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Cheating from a Distance: An Examination of Academic Dishonesty Among University Students

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CHEATING FROM A DISTANCE: AN EXAMINATION OF ACADEMIC DISHONESTY AMONG UNIVERSITY STUDENTS

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DEDICATION

This dissertation is dedicated to my mom (Bernardita) and dad (Michael), both of whom have shown me unconditional love, patience, and encouragement my entire life. Their support made it possible for me to pursue this Ph.D. and complete this dissertation.

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ABSTRACT

Academic dishonesty among college students has been an enduring issue within higher education. While prior research has explored this issue, the recent global pandemic has shifted collegiate demographics dramatically, particularly within online courses. As a result, previous findings may prove less applicable, warranting new research into student cheating within this current educational landscape. Given these new enrollment trends, this study investigated intentions to cheat in traditional and online class settings, and for criminal justice and non-criminal justice majors. Utilizing principles of rational choice theory, other factors related to academic misconduct also were explored.

For this study, original data were collected from one institution in the New England region of the United States. An online questionnaire was emailed to approximately 6,900 undergraduate and graduate students, resulting in 1,084 total submitted surveys. Using the email link, participants were assigned randomly to treatment and control groups based on course modalities. More precisely, 553 students responded to prompts related to cheating in traditional courses, while 531 students answered similar questions related to online courses. Using the obtained data, a series of univariate, bivariate, and multivariate statistical results were produced.

The results of the statistical models yielded numerous significant findings regarding influences on academic dishonesty among college students. Among these results, three findings were especially noteworthy. First, intentions to cheat appear relatively equivalent among traditional and online students. While certain distinctions were observed among online students, overall cheating behaviors were quite similar across the course groups. Second, criminal justice majors reported more concerning levels of academic misconduct than initially suspected. While cheating appeared similar across all academic majors, criminal justice students reported higher intentions to cheat in certain scenarios. Finally, perceptions of cheating benefits yielded the most

consistently significant results among the rational choice variables. Overall, academic dishonesty was more likely to occur when such behaviors were perceived to positively affect a student's academic, peer, and/or familial goals. This study reveals the significant factors influencing the likelihood of academic dishonesty, followed by a discussion of policy implications to remedy this issue and suggestions for future research.

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CHAPTER ONE

Introduction

The landscape of higher education has changed considerably in modern times. New innovations in technology have been especially transformative, as evidenced by the amount of online resources made available to students and faculty (McCabe et al., 2012; Stogner et al., 2013). Moreover, this integration of digital and electronic resources had a tremendous impact on online education. Over the last decade, enrollment in online courses grew rapidly among collegiate institutions (Seaman et al., 2018). Specifically, the demand for online courses is the fastest growing market within the higher education system (Protopsaltis & Baum, 2019). Among collegiate administrators in 2015, roughly 70% reported that growth of their remote learning programs was a fundamental goal for their respective institutions (Allen & Seaman, 2015). While higher education observed many positive outcomes through this integration, unintended consequences also surfaced. More precisely, interest and concern about college student cheating increased substantially with the availability of online education and information (Stogner et al., 2013).

Generally speaking, academic dishonesty can be characterized by a host of behaviors, such as copying answers from a classmate, using material in a paper without proper citations, or collaborating with other students on an assignment (McCabe et al., 2012). However, variants of test cheating and plagiarism are considered the most widely practiced forms of academic misconduct (Hensley et al., 2013; McCabe et al., 2004; McCabe et al., 2012). Research has determined that advancements in technology have had a significant impact on student learning behaviors (Lanier, 2006; Stogner et al., 2013). These advancements have been particularly pertinent within academic dishonesty research, as the internet has had a particularly powerful effect on student cheating (Stogner et al., 2013). One fairly recent study estimated 40% of

students had used the internet to facilitate academic misconduct (Stogner et al., 2013). By potentially enabling more cheating behaviors among college students, modern technology has further exacerbated the issue of academic misconduct (Lanier, 2006; McCabe et al., 2012; Rowe, 2004; Stogner et al., 2013; Watson & Sottile, 2010).

In general, high rates of cheating may reflect overall student perceptions concerning the seriousness of academic dishonesty. For college students, exhibiting widely favorable views towards this form of misconduct is quite common (Bernardi et al., 2008). To illustrate, in one sample, 39% of college students considered "cut and paste" plagiarism an acceptable behavior within courses (McCabe et al., 2012). While this poses a concern for university officials, these perceptions also may have long-term implications for workforce behavior. Specifically, unethical behaviors during college may predict future behaviors during adulthood.

Sims (1993) asserted that academic misconduct extends beyond the situational factors that students endure during college. Rather, a student's willingness to engage in cheating may be more indicative of a dishonest nature. If academic misconduct was isolated to situational factors within the collegiate setting, students would cease these dishonest actions upon graduation. Unfortunately, students who engaged in more serious academic dishonesty often mirror those behaviors within professional settings (Sims, 1993). This is particularly concerning for criminal justice departments. Criminal justice majors are often trained for professional positions in public service and enforcement. As such, a higher level of integrity and morality often is expected. The conclusions from Sims (1993) would suggest that unethical behaviors during college could reverberate well into a student's professional career. As such, widespread acceptance of cheating may pose a systemic threat to both higher education (Bernardi et al., 2008; Keith-Spiegel et al., 1998) and society (McCabe, 1999). As such, it is imperative for researchers and university

officials to fully investigate this issue and identify effective strategies that mitigate academic misconduct.

The purpose of this study was to investigate cheating behaviors within traditional classroom and online settings, and to determine possible distinctions in cheating behaviors between criminal justice and non-criminal justice majors. To fully examine this topic area, previous literature concerning academic dishonesty initially was reviewed. After considering these prior studies, an appropriate methodology and theoretical framework were chosen for the current research. Original data was collected through use of an online survey, generating 1,084 responses. Furthermore, rational choice theory was identified as the most appropriate framework for guiding the research and analysis. In developing survey items, variables were designed to reflect the different dimensions of academic dishonesty, the theoretical principles of rational choice theory, and individual characteristics among college students. Once collected, the data underwent a series of quantitative analyses to examine factors that influence academic dishonesty in both traditional and online courses.

Summary of Prior Literature

With respect to existing literature, academic dishonesty among college students has been researched by various investigators. Cheating research specific to online students is more limited, however (Watson & Sottile, 2010). Remote learning is still a relatively new practice among institutions of higher education. As such, research studies examining online student behaviors only have surfaced during the past few decades. Nonetheless, several studies have examined academic misconduct in remote environments and assessed how cheating rates compare with those of on-campus classes.

In an early study by Lanier (2006), cheating rates were examined among two groups of students: in-person attendees and remote learners. Students in this sample were asked to self-

report past cheating behaviors in their respective courses. Upon examination of the data, Lanier (2006) determined that participants belonging to the online group reported a higher rate of cheating than participants in traditional instruction. While this study showed higher academic dishonesty within remote courses, subsequent research would report contrary results concerning cheating within online education.

To illustrate, another early study was conducted by Grijalva and colleagues (2006), where cheating rates were calculated among a group of online college students. Specifically, the researchers collected data that estimated student likelihood of cheating in one online class. Overall, the results yielded no evidence that an online learning environment invites higher rates of academic misconduct (Grijalva et al., 2006). Additionally, the researchers argued that the concern for increased cheating in online courses is unwarranted. Specifically, they asserted that increases in online education enrollment will not necessarily result in an influx of student cheating (Grijalva et al., 2006). According to these authors, any predictor variables that impact cheating behaviors in an online course would likely apply within an in-person setting as well. Furthermore, the online environment may prove less conducive to cheating, since students may experience fewer stressors in the remote setting (Grijalva et al., 2006).

While it is still commonly believed that the growth in online learning will result in increased cheating behaviors, further review of the existing research would question this claim. Many prior studies have yielded findings that directly refute this misconception, arguing that students in an online environment actually cheat less than traditional students (Harmon et al., 2010; Stuber-McEwen et al., 2009; Tolman, 2017; Watson & Sottile, 2010). These findings may be attributed to anti-cheating software often employed by universities.

While easy access to internet resources has intensified the issue of cheating, technological advancements also have improved detection methods for instructors (Bruton &

Childers, 2016; McCabe et al., 2012). Specifically, software such as Turnitin® has improved faculty capabilities in detecting incidents of plagiarism. Through Turnitin®, student submissions are automatically evaluated for possible academic misconduct. As previously noted, “cut and paste” plagiarism is an especially common practice among modern college students (McCabe et al., 2012). However, Turnitin® easily can identify and mark such portions for instructors to review. The Respondus Lockdown Browser also has been quite useful to online instructors. Through the Respondus program, students are prohibited from opening web browsers while taking an exam. In general, use of this program can alleviate some concerns over unproctored examinations in online courses (Stack, 2015). Use of these programs may also influence formal reporting of cheating my college instructors.

According to Staats and associates (2009), college instructors often report “insufficient evidence” as a key hesitation when considering formal charges of cheating (Staats et al., 2009). For many instructors, proving that a student has engaged in academic dishonesty is a challenge. However, this concern may prove less prominent when software produces adequate evidence. With increased confidence in the evidence, higher rates of formal sanctioning may result (Beasley, 2016; Staats et al., 2009). Overall, existing research findings are quite promising, suggesting a gradual improvement in online course development and delivery.

Based on these findings, it appears as though modern institutions have created online environments where academic misconduct is less appealing to college students. Moreover, a growing number of students may be regarding online education as an equivalent learning experience to in-person courses. In one sample of students, Harmon and colleagues (2010) reported that 59% of students believed that academic dishonesty was similar across in-person courses and online courses. This would imply that a large proportion of students perceive the online educational environment to be parallel to traditional classroom instruction.

Limitations of Previous Research

While prior evidence would suggest that academic dishonesty is less concerning within remote learning, this issue is still worthy of further review. Specifically, changes to higher education delivery over the past year must be considered. In response to the 2020-2021 Covid-19 pandemic, enrollment figures concerning online matriculation have shifted considerably. Prior to this pandemic, remote learners represented a minority of college students. Specifically, when analyzing enrollment data from 2015, students taking at least one distance course only represented 29.7% of the college student population (Allen & Seaman, 2017).

In general, the environmental dynamics of online courses are noticeably different from traditional courses (Jaggars & Xu, 2016; Stuber-McEwen et al., 2009; Sun & Chen, 2016). As such, these learning distinctions within online courses typically appealed to specific groups of students. Previously, students who participated in online courses often were dissimilar to the average college student (Bernard et al., 2014). More precisely, online courses generally attracted non-traditional and older groups of students (Coates & Humpreys, 2004; Harmon et al., 2010; Jaggars & Xu, 2010), and colleges observed a growing demand for online learning among those student groups. This could be attributed to reduced tuition costs and schedule flexibility. For non-traditional students, college attendance may be balanced against employment, familial obligations, or both. As such, online education appeared particularly appealing, as it enabled these individuals to create unique learning schedules. When analyzing studies conducted prior to 2020, non-traditional students likely were overrepresented when examining online student behavior.

Traditionally, most on-campus college students elected in-person courses during their collegiate tenure. However, the recent and current state of the pandemic has led to many obstacles with the reopening of colleges and providing courses in traditional settings.

Consequently, many colleges have significantly altered on-campus operations for students. In the fall 2020 semester, only 4% of American colleges offered only in-person courses ("Our List of College Reopening", 2020). In contrast, roughly 44% of colleges shifted to a fully online or predominantly online model of course delivery for that same semester. This was a sharp departure for not-for-profit institutions that previously relied heavily on in-person instruction.

Generally speaking, the historical effects of the Covid-19 pandemic seem to have had a significant influence on the state of online education. As such, previous findings concerning remote learners may prove less applicable among current cohorts of students. Furthermore, online courses currently have much greater diversity in student enrollment, which would warrant new research into academic dishonesty among remote learners.

The Current Study

The findings from the current research should generate policy implications for both online education and criminal justice departments. The recent pandemic has caused educational practices to shift dramatically across collegiate institutions. In response, colleges have embraced predominately online modalities for course deliveries. Through this study, academic dishonesty for both traditional and online students was explored. Unlike earlier studies that examined online cheating, this current study investigated cheating among a more diverse group of remote learners. During the pandemic, a much larger proportion of traditional students enrolled in some form of online learning for the 2020 – 2021 academic year. As such, new insight concerning the effectiveness of online courses across different student groups can be derived.

In addition, this study contributes new knowledge and policy guidance for criminal justice programs. Academic dishonesty is a concerning issue, as it speaks to the ethical orientations of students. For criminal justice majors, a lower incidence of cheating generally is expected, as these students often enter professions that require higher levels of integrity.

Unfortunately, previous research has suggested that the cheating behaviors of criminal justice majors appear quite similar to all university students (Eskridge & Ames, 1993; Lambert & Hogan, 2004). Moreover, prior studies have identified peer relationships as especially influential among these criminal justice majors (Lambert & Hogan, 2004; Tibbets, 1998). As such, peer influences was a central variable utilized during statistical analyses.

In sum, this study should provide valuable insight concerning academic dishonesty and the current cheating behaviors of college students. In Chapter 2, a thorough review of previous cheating literature is presented, including an overview of relevant factors that appear to influence academic misconduct among college students. This chapter also points to the theoretical discussions provided in Chapter 3. Criminological theories have strong application within studies of college student cheating. Chapter 3 contains an overview of relevant criminological theories and discusses how components of rational choice theory will be applied within the current research. In Chapter 4, this study's methodology is presented. This includes information concerning this study's sampling strategies and development of variables. Chapter 5 presents the results of the research. Following data collection, survey responses underwent a series of univariate, bivariate, and multivariate analyses. Through these statistical techniques, new findings concerning academic dishonesty among modern college students were derived. Finally, Chapter 6 provides a summary and conclusion, where key findings, limitations, policy implications, and directions for future research are presented.

CHAPTER TWO

Academic Dishonesty among College Students

Academic dishonesty among college students has been an enduring issue within higher education. Overall, research conducted during the past half-century has revealed a large proportion of college students engage in academic misconduct during their university tenure (Bowers, 1964; Hodgkinson et al., 2016: Lambert & Hogan, 2004; Tibbetts & Myers, 1999). At the time of Bowers' (1964) early and large multi-site study, academic misconduct was a widely understated issue among university administrators. Through his research, Bowers (1964) exposed widespread cheating behaviors across college campuses. Specifically, Bowers (1964) revealed that 83% of college students had engaged in some form of test cheating, homework cheating, and/or plagiarism. Following these early findings, however, substantial attention given to this issue only surfaced within more recent decades (Davis et al., 1992; McCabe et al., 2012).

Using similar survey items first introduced by Bowers (1964), McCabe and colleagues collected student cheating data over the course of thirty years (McCabe et al., 2012). Over time, the prevalence of academic dishonesty appears to have remained relatively stable among college students (McCabe et al., 2012). A large proportion of college students still report engagement in at least one form of test cheating, homework cheating, or plagiarism (McCabe et al., 2012). Based on data collected during 2002 to 2010, McCabe and colleagues (2012) determined that copying sentences into papers (36%), collaborating on homework assignments (42%), and retrieving exam questions from a classmate (30%) were the most common forms of cheating among a sample of 73,738 students.

To fully examine this issue, this chapter will discuss factors that contribute to academic cheating among college students. Over the years, researchers have identified a host of variables that have proven influential to college student cheating. However, educational practices have

shifted dramatically in response to the pandemic, likely influencing previously identified cheating factors. As such, revisiting the previously studied independent variables and assessing their statistical significance in the current educational context is warranted.

Factors in Academic Misconduct

While research already has established that academic misconduct is widespread across collegiate institutions, identifying key explanatory variables or student risk factors may strengthen knowledge of the topic and generate effective prevention and intervention strategies. Prior studies have examined a multitude of influences on student cheating behaviors. Among these variables, researchers have published notable findings on the impact of high school experiences (McCabe et al., 2012; Stuber-McEwen et al., 2009), course type (Tolman, 2017; Watson & Sottile, 2010), academic major (Lambert & Hogan, 2004; Tibbetts, 1998), peer relationships (McCabe et al., 2012; McCabe & Trevino, 1993; 1997), gender (Whitley et al., 1999; Whitley, 2001), age (Haines et al., 1996; Lambert & Hogan, 2004), academic achievement (Stuber-McEwen et al., 2009), and international status (Beasley, 2016; Simpson, 2016).

High School Cheating Experiences

In general, studies on high school student behavior have proven useful in considering and assessing collegiate cheating. While academic misconduct is a widespread issue among college students, rates among high school students also are concerning (Jensen et al., 2002; McCabe et al., 2012; Stuber-McEwen et al., 2009). Specifically, research has revealed that cheating behaviors are quite common among high school populations, perhaps in even greater magnitude than in college populations (Davis et al., 1992; Jensen et al., 2002; McCabe et al., 2012; Stuber-McEwen et al., 2009). Though the experiences of high school and college education are similar in some ways, McCabe and colleagues (2012) suggest that high school students encounter unique stressors that may encourage academic misconduct. These stressors can include parental

influences, meeting or exceeding academic expectations, and poor relationships with teachers (McCabe et al., 2012). As such, exposure to cheating behaviors may first surface during high school (or earlier) and subsequently persist during a student's college career (McCabe et al., 2012; Stuber-McEwen et al., 2009).

Initiation into Academic Dishonesty

For certain research, pinpointing the initiation period of entry into cheating has been a central inquiry. In one study, Brandes (1986) examined the comparability of cheating rates among elementary school students and high school students. Using self-reported data, Brandes (1986) observed several notable distinctions between these two age groups. Specifically, high school students were more likely to engage in academic misconduct than their younger counterparts. Additionally, perceptions towards cheating appeared different across these students. When asked about the acceptability of cheating among their classmates, the majority of high school students reported that such behaviors were considered permissible. This contrasted with the views of elementary school students, where the majority of participants held an opposing view. With such differences shown between elementary and high school students, the finding of this study suggested that widespread academic misconduct is likely to surface during high school.

This topic was examined further by Anderman and Midgley (2004). Using longitudinal data, the authors examined student perceptions at different levels of education. Consistent with the findings of Brandes (1986), these researchers hypothesized that the transition to high school would alter student behaviors, leading to higher rates of self-reported cheating. Analysis of the data corroborated this hypothesis. The results indicated that student cheating behaviors remained relatively low and stable through eighth grade. However, transition to high school dramatically

changed student attitudes towards academic dishonesty. Furthermore, following entrance into high school, students reported greater participation in test misconduct and assignment copying.

Overall, these findings imply that college student cheating may stem from certain behaviors established during high school. Based on these findings, further research into this population of students would appear warranted. Unfortunately, research concerning high school cheating has been fairly limited (McCabe et al., 2012). Rather, college student populations appear more central within academic dishonesty studies (McCabe et al., 2012).

Changing Trends

Despite somewhat limited research, available studies do suggest that cheating appears to be a widespread issue among secondary schools. Moreover, high school student behaviors appear to have changed considerably since the 1960s. Using 30 years of longitudinal data, Schab (1991) determined that high school students developed more permissive attitudes towards academic misconduct, and increases in high school cheating were quite concerning. In 1969, 33.8% of high school students admitted to academic dishonesty. In 1979, this cheating rate increased to 59.5% among high school students. By 1989, 67.8% of the sampled high school students had admitted to prior engagement in academic dishonesty.

Overall, this high rate of cheating has remained relatively stable among secondary schools. In a nationally representative sample of high school students, excessive cheating was self-reported among the participants (Josephson Report Card, 2012). Nearly 50% of the high school respondents had reported test cheating, while 75% of respondents had admitted to copying homework assignments from classmates. Even more troubling, roughly one third of respondents believed that cheating was a necessary action for success in life. McCabe (1999) uncovered similar viewpoints concerning cheating and life success. Among a sample of high school students, academic dishonesty was not considered a serious offense. Rather, for these

students, academic misconduct was a widely normalized behavior. In general, high school students felt that cheating was a natural life event that would continue to persist in society (McCabe, 1999). These viewpoints would seem to warrant greater urgency in the development of preventative measures. Among known preventative measures, shifts in teaching strategies may alter cheating rates among high school students.

Classroom Structure

For high school students, classroom structure has a significant influence on academic dishonesty. In situations where a poor learning environment is established, cheating can become a frequent occurrence (McCabe, 1999; Murdock et al., 2004; Murdock et al., 2008). When asked about previous cheating incidents, students most commonly cite teacher behaviors as major drivers (Murdock et al., 2008). For example, teacher apathy appears to influence student perceptions toward academic misconduct (Murdock et al., 2008). More specifically, such environments may cause students to adopt a more favorable opinion towards classroom dishonesty (McCabe, 1999; Murdock et al., 2004; Murdock et al., 2008).

While teacher attitudes are important, cheating may occur more often when students are inadequately taught. According to Murdock and colleagues (2004), students often gain more favorable impressions of cheating when exposed to poor educational instruction. Furthermore, these researchers determined that three major factors appear to impact such impressions: poor teaching skills, overemphasis on performance goals, and teacher apathy towards student success (Murdock et al., 2004). In these situations, students are less likely to take ownership for academic cheating and are more likely to channel the blame towards their teachers. Among college student populations, similar arguments also have been established. For college instructors, creating a positive learning environment can yield more impressive outcomes among

students (Jaggars & Xu, 2016; Kuo et al., 2013; Sun & Chen, 2016). As such, changes in classroom practices may prove beneficial across high schools and colleges.

In sum, research suggests that high school experiences can set students on a trajectory for collegiate cheating (McCabe et al., 2012; Stuber-McEwen et al., 2009). In general, high school students often have non-serious attitudes towards academic dishonesty (McCabe et al., 2012). In establishing this mindset early on in life, these attitudes may reverberate through college and adulthood. As such, addressing this issue among secondary schools may prove beneficial to higher education. In essence, lower cheating rates among high school students could lead to similar reductions among college students.

Course Type (Online Learning)

In recent years, greater attention has been given to the use of online courses and associated academic dishonesty. Within online classes, academic dishonesty can be influenced by the established course design of an instructor. For example, some prior research suggests that cheating behaviors appear less prevalent in online courses than in traditional courses (Tolman, 2017). These lower rates of cheating could be attributed to the preventative measures of online instructors. With cheating behaviors in mind, instructors may design certain assignments to avoid such situations from occurring (Tolman, 2017).

Course Assessments

Watson & Sottile (2010) conducted a study that analyzed this topic in more depth. While these researchers concurred that overall cheating is lower within remote courses, several considerations must be noted among instructors. Watson & Sottile (2010) determined that certain types of cheating might occur more often within a remote context. For example, the remote nature of an online class may enable more incidents of test cheating. When tests were delivered remotely, students often obtained answers from fellow classmates prior to the exam period

ending. This occurrence mirrors common concerns with exams and cheating in traditional classrooms. Since exams may be unproctored in an online class, students consequently behave differently than if they physically took an exam in the presence of their instructor.

As online education continued to grow in prominence, Watson & Sottile (2010) encouraged caution when assigning online tests. They suggested that open-ended written assessments should be assigned in lieu of closed-ended test questions. Harmon and colleagues (2010) corroborated this finding, arguing that multiple choice exams invite greater cheating behaviors within the remote environment. Nonetheless, online instructors seem to trust remote testing as a primary form of grading. In analyzing the course design of 20 online courses, it was discovered that 70% of these courses relied heavily on unproctored multiple-choice exams for assessment purposes (Harmon et al., 2010). This popularity in online examinations may be facilitated by the automated grading systems available to faculty. Regardless, researchers argue that online instructors should reconsider multiple choice exams within an online course (Harmon et al., 2010; Watson & Sottile, 2010). The physical distance between instructors and students also should be considered in other components of online course development.

Remote Learning Environments

With respect to online courses, the physical distance between instructors and students is often criticized among opponents of remote learning (Stuber-McEwen et al., 2009; Sun & Chen, 2016). For traditional courses, students regularly interact with instructors, which can lead to stronger educational relationships. However, this proves more challenging among individuals in an online course. While remote learning does physically remove students from the traditional classroom, research suggests that online students still benefit from a strong sense of community (Jaggars & Xu, 2016; Kuo et al., 2013; Sun & Chen, 2016). More precisely, academic achievement is higher among students who foster strong interpersonal communication within

online classes (Jaggars & Xu, 2016). In addition, student satisfaction is also highly correlated with interpersonal relationships (Kuo et al., 2013).

For these goals to be achieved, instructors must actively cultivate positive interactions with students (Jaggars & Xu, 2016; Kuo et al., 2013; Sun & Chen, 2016). Unfortunately, establishing a sense of community is a common challenge for online lecturers (Sun & Chen, 2016). While these instructors play a fundamental role in the classroom environment, Sun & Chen (2016) argue that students must also contribute to the course environment. More precisely, students must be actively engaged with both their peers and the instructor. In the absence of motivated students, online class success may be impacted.

In general, achieving positive classroom environments within online courses is rarely achieved (Sun & Chen, 2016). This change in classroom environment may be particularly prudent in issues such as academic dishonesty. Since online education can yield weaker relationships among students and instructors, the risk for academic dishonesty is heightened (Stuber-McEwen et al., 2009). Previous research indicates that classroom structures established by instructors can influence student behavior (Tibbetts, 1998; Tibbetts & Myers, 1999). In promoting course environments that highlight integrity and learning, instructors can reduce the level of student cheating (Tibbetts, 1998; Tibbetts & Myers, 1999). As such, applying this principle into a remote learning environment should be examined further.

Distinct Course Development

Online course development also has a significant impact on student behaviors and outcomes. Prior research reveals that the development of effective online courses takes a greater time commitment from instructors (Allen & Seaman, 2013; Sun & Chen, 2016). Unfortunately, institutions often consider time commitments for online teaching to be lower or comparable to in-person teaching. As a result, instructors are given larger workloads with limited support. In

response, instructors may simply adapt traditional teaching methods into an online course. According to Jaggars & Bailey (2010), this is a common practice among online professors. Rather than utilize digital resources, instructors often use in-class techniques within a remote setting. However, this approach may prove inferior within online education.

In one study, Figlio and colleagues (2010) compared learning outcomes among two groups of college students. In one group, the students were exposed to live class lectures from the professor, while the other group of students were offered recordings of these live lectures. In general, the delivery of lectures was the major distinction among the two groups. When comparing student performance among these two groups, the students in the live lectures achieved more impressive scores (Figlio et al., 2010). While this may suggest an inferiority of online education to traditional lectures, it more likely implies that traditional teaching techniques cannot be simply adapted within an online course. Instead, innovative teaching techniques may need to be developed within online education.

An online course typically has prominent distinctions when compared to a traditional class. Among these distinctions is the reliance on technology and teaching innovation (Allen & Seaman, 2015; Lanier, 2006). According to Allen and Seaman (2015), instructor familiarity with online technologies can have an important impact on remote learning. As previously mentioned, teaching online requires a greater time commitment (Allen & Seaman, 2013; Sun & Chen, 2016). More precisely, it takes time for instructors to develop new skills that are well-suited for online delivery (Allen & Seaman, 2015). Unfortunately, a reluctance to innovate may impede the overall success of online education. In turn, this may also impact the incidence of cheating among online students. According to Kuo and colleagues (2013), student satisfaction within an online course is highly motivated by the quality of course content delivered. For online students who feel inadequately taught, it is possible that lower satisfaction could impact academic

dishonesty rates. As such, online instructors must recognize the inherent differences within a remotely taught course. When properly developed, online education may observe notable improvements in quality and student cheating rates.

Academic Major

In studying academic misconduct among college students, researchers often examine the influence of individual characteristics. Specifically, they have hypothesized that certain attributes may greatly impact a student's decision to cheat (Coston & Jenks, 1998; Eskridge & Ames, 1993; Lambert & Hogan, 2004; Tibbetts, 1998). Among these attributes, choice of major has been a central variable for analysis. While this research is limited, several researchers have posited that academic misconduct may be less prevalent among certain academic disciplines. In particular, it has been hypothesized that the incidence of cheating should be lower among criminal justice students (Eskridge & Ames, 1993; Tibbetts, 1998). For criminal justice majors, collegiate coursework generally prepares these students for careers within the justice system. As such, an examination of ethics often is included within a criminal justice curriculum (Byers & Powers, 1997; Coston & Jenks, 1998; Tibbetts, 1998). In preparing for future positions, a higher degree of morality and ethics typically is expected (Coston & Jenks, 1998; Eskridge & Ames, 1993; Tibbetts, 1998). This presumption inspired several empirical studies, leading researchers to investigate distinct behaviors among criminal justice majors (Coston & Jenks, 1998; Eskridge & Ames, 1993; Lambert & Hogan, 2004; Tibbetts, 1998).

Behaviors among Criminal Justice Majors

In general, past research into academic misconduct among criminal justice majors is fairly limited. However, several past studies have identified certain behavioral distinctions. Using a sample of undergraduate criminal justice majors, Coston and Jenks (1998) examined the motivations and prevalence of cheating behaviors among these students. In developing their

study, the researchers hypothesized that criminal justice majors would engage in less academic misconduct than the general population of students. They derived this hypothesis partly because criminal justice majors are trained for careers where ethics and morality are especially prudent. Specifically, future decision making could be correlated with the cheating behaviors that students exhibit during college.

In gathering self-reported data from these criminal justice majors, the data revealed that 51% of these participants had engaged in past academic misconduct. Although this appears to be a high participation rate, the authors actually advanced this as a promising statistic. Compared to previously reported levels of student cheating, Coston & Jenks (1998) uncovered a lower engagement rate among criminal justice majors. As such, they claimed empirical support for their initial research hypothesis. However, the accuracy of this statement could be called into question. Coston & Jenks' (1998) study suffered from a major methodological shortcoming: the sample only included criminal justice majors at one university. Adding non-criminal justice majors could have strengthened the validity of these research findings. Specifically, a comparative research design could have determined whether all students at this university engaged in less cheating than the nationally reported averages. Furthermore, the sample size was relatively small. Using a group of 102 criminal justice majors, the researchers compared the cheating rate of this group against samples with significantly higher participants. As such, based on their study, it is difficult to assert that the incidence of cheating is significantly lower among criminal justice majors.

Other research suggests the overall incidence of academic misconduct among criminal justice majors appears similar to the general population of students (Eskridge & Ames, 1993; Lambert & Hogan, 2004). Eskridge and Ames' (1993) study was one of the earliest projects to examine the relationship between criminal justice majors and academic dishonesty. While other

research had explored cheating among different academic majors, Eskridge & Ames (1993) specifically identified criminal justice majors as their principle population.

Through this study, the researchers examined attitudes towards cheating among a group of 639 undergraduate students from one university. The sample was comprised of a diverse group of academic majors, with 25% of the participants majoring in criminal justice. In collecting self-reported data, the researchers sought to identify distinctions among criminal justice majors. As previously mentioned, criminal justice majors often enter fields where higher moral character is desired. This assumption guided the initial hypothesis of Eskridge and Ames (1993), leading them to predict that criminal justice majors would engage in fewer incidents of cheating.

However, the findings from this study did not support this hypothesis. The analysis indicated a relative equivalence across criminal justice and non-criminal justice majors. While the researchers expected lower involvement in cheating among criminal justice majors, the findings suggested that academic misconduct was widespread across all majors. For both groups of students, nearly 95% of the participants had engaged in at least one cheating incident during their collegiate tenure. Moreover, many students reported multiple incidents of past cheating while attending college. As such, the researchers concluded that academic major was not a significant determinant of academic dishonesty.

These findings suggested an area for concern within criminal justice studies. As Eskridge and Ames (1993) noted, criminal justice graduates will assume roles in society where strong ethics are expected. While this study specifically analyzed collegiate cheating behaviors, the researchers asserted that such unethical behaviors could be indicative of future professional practice. However, they also reported several promising statistics emerging from their data. Criminal justice majors had slightly less favorable views of cheating. In addition, these students

also reported lower rates of academic misconduct in the past year. While these were promising findings, they failed to reach statistical significance. More accurately, the differences between the two groups of majors were minimal.

In a subsequent study, Tibbetts (1998) also examined behavioral distinctions between criminal justice and non-criminal justice students. Adopting principles from control and rational choice theories, Tibbetts (1998) analyzed how specific variables influence a student's likelihood to cheat on an exam. In designing his study, Tibbetts (1998) collected scenario-based survey data from a sample of 330 college students. The participants were presented with a series of hypothetical situations and were asked to report personal responses to such situations. Consistent with the research findings of Eskridge & Ames (1993), the results suggested that criminal justice and non-criminal justice majors expressed similar cheating behaviors. Consequently, Tibbetts (1998) also expressed disappointment in such findings, as the results suggested that cheating was fairly widespread and unrelated to the academic focus of the students. In addition, three explanatory variables proved statistically significant for predicting cheating intentions among all student majors: anticipated feelings of shame, a moral belief that cheating is wrong, and experiences with cheating in the past year (Tibbetts, 1998). Feelings of shame and moral beliefs had a negative relationship with cheating intentions, while experiences with past year cheating had a positive relationship.

Based on this research, although being a criminal justice major appears to have minimal influences on cheating rates, broadening the academic major variable may prove important for studying academic dishonesty. In Lanier's (2006) study of traditional and online students, academic major was considered as a predictor variable for academic dishonesty. However, students were grouped as social science majors and non-social science majors. Upon analysis of the results, social science majors had a higher likelihood of academic dishonesty. Since previous

findings found no differences among criminal justice students, it is possible that students in other social science disciplines display greater inclinations towards academic misconduct. In this context, criminal justice majors actually may exhibit fewer incidents of cheating when compared to similar majors.

Lanier (2006) also observed certain distinctions among social science students in traditional and online courses. Among students in traditional courses, being a social science major had a statistically significant impact on cheating behaviors. However, the impact appeared more subdued among online students. For online students, being a social science major did not significantly influence academic misconduct. As such, the influence of academic major on cheating may be moderated by the modality of course delivery. For future studies, analyzing how different majors behave in online courses may prove valuable to academic dishonesty research.

Other Distinctions among Criminal Justice Majors

Some research has produced evidence indicating how students majoring in criminal justice can be distinguished from other college students (Eskridge & Ames, 1993; Lambert & Hogan, 2004; Tibbetts, 1998). In general, these studies have identified certain variables that are more pronounced among criminal justice students. Tibbetts (1998), for instance, noted specific behavioral distinctions among criminal justice majors and non-majors. First, perceived pleasure appeared to be quite different for criminal justice students. More specifically, criminal justice majors seemed to derive less pleasure from cheating when compared to non-majors. Second, while moral beliefs proved statistically significant among majors and non-majors, the strength of this influence was quite different. In both groups, a person's moral belief that cheating was wrong appeared to have a negative relationship within academic misconduct. However, the data indicated that a stronger effect was observed among non-criminal justice majors. Lastly, the impact of peer relationships on criminal justice students was a particularly important finding.

While peer relationships proved insignificant among non-criminal justice majors, the study reported a significant and positive effect among criminal justice majors. According to Tibbetts (1998), intentions to cheat among criminal justice majors seemed more highly influenced by the behaviors of their peers. This finding for peer relationships was substantiated in Lambert and Hogan's (2004) research as well.

Lambert and Hogan (2004) utilized self-reported data from 850 university students. The participants belonged to a wide range of academic majors, which allowed for more direct comparisons to criminal justice majors. Through a survey, students were asked about their past experiences with cheating and specific justifications they held towards academic misconduct. Similar to Tibbetts (1998), Lambert and Hogan (2004) noted several behavioral distinctions among students who major in criminal justice. Most notably, academic diligence and peer influences were especially distinctive among criminal justice students. For academic diligence, criminal justice majors often sought strategies to expedite coursework. For example, when given a long reading assignment, criminal justice majors were more likely to read condensed versions of the material (Lambert & Hogan, 2004). In other words, academic shortcuts were more appealing to criminal justice majors. Additionally, the impact of peer relationships was quite important. As first reported by Tibbetts (1998), criminal justice majors appeared more easily influenced by the behaviors of their fellow peers. In response to these peer influences, criminal justice students were more likely to take exams for classmates (Lambert & Hogan, 2004).

This latter finding seems particularly concerning for the field of criminal justice. Specifically, it suggests that criminal justice professionals may behave unethically when peer influences demand such behaviors (Lambert & Hogan, 2004; Tibbetts, 1998). On the other hand, while Lambert and Hogan (2004) identified certain negative behaviors among criminal justice majors, they also noted several positive distinctions. For instance, criminal justice majors were

more likely to cite references correctly. When developing bibliographies for written assignments, these students displayed a lower likelihood of creating false sources. Relatedly, criminal justice majors also displayed greater autonomy in completing assignments. In general, these students were less likely to engage in prohibited activities like referencing past exam questions and working collaboratively on an independent assignment. As such, distinctions among criminal justice majors may be more evident when specific components of cheating are analyzed.

Peer Relationships

For college students, peer relationships have a strong impact on individual behaviors (McCabe et al., 2012; McCabe & Trevino, 1993; 1997). Among these behaviors, engagement in cheating is driven acutely by the influences of classmates and peers (McCabe et al., 2012; Staats et al., 2009). For example, students often observe the actions of classmates and peers. In a situation where cheating is consistently unpunished, this may encourage similar conduct among other students (McCabe et al., 2012; McCabe, 1992). In general, this mode of thinking is aligned within a rational choice framework. In certain circumstances, decisions to cheat are rationally derived choices among college students (Staats et al., 2009).

Within online courses, peer influences may prove less significant to academic misconduct. As previously discussed, remote learning is quite distinct from traditional education. Students are afforded greater autonomy in course completion, possibly limiting social interactions with other students. Overall, strong collaboration between students is rarely achieved in online courses (Sun & Chen, 2016). Furthermore, multiple observations of peer cheating within a remote learning structure is unlikely. As such, personal interactions among online students may prove less meaningful, thus weakening the potential strength of peer influences.

As previously discussed, the influence of peers is particularly pronounced among students majoring in criminal justice. For the overall cheating rates between criminal justice

majors, minimal differences have been reported when compared against the general population of students (Eskridge & Ames, 1993; Lambert & Hogan, 2004). However, the influence of peers on academic dishonesty is a notable exception (Lambert & Hogan, 2004; Tibbetts, 1998). Criminal justice majors appear more susceptible to cheating when a peer promotes such behavior. In examining this interaction effect more closely, academic dishonesty prevention and intervention strategies could benefit from the findings.

Gender

While academic dishonesty appears widespread across college student populations, a student's gender may have a relationship with such behaviors. For many studies, cheating distinctions between male and female students have received considerable research attention (McCabe et al., 2012). From a historical context, early studies concluded that academic misconduct was more prevalent among male students (Bowers, 1964; Davis et al., 1992; McCabe & Trevino, 1997; Pino & Smith, 2003; Tibbetts & Myers, 1999; Whitley et al., 1999). Even among high school populations, these gender distinctions were observed (Davis et al., 1992). Among the studies on gender and collegiate academic dishonesty, the research conducted by Whitley, Nelson, and Jones (1999) was especially noteworthy.

At this point in history, few studies comprehensively examined the relationship between these two variables. To remedy this oversight, the authors conducted a meta-analysis to fully explore this issue (Whitley et al., 1999). Collecting research from 48 previous research articles, the researchers sought to identify notable distinctions between male and female students. Whitley, Nelson, and Jones (1999) hypothesized that male students would exhibit more favorable opinions towards academic dishonesty, which would lead to a higher incidence of cheating. As such, student attitudes and behaviors were key outcome variables within this study.

Through statistical analysis, gender distinctions were observed in attitudes and behaviors towards cheating. Overall, males possessed more favorable attitudes towards cheating. Statistically, this gender distinction produced a medium effect size (Whitley et al., 1999). Additionally, higher engagement in academic dishonesty was observed among the male students. However, the reported effect size for this relationship was much smaller (Whitley et al., 1999). The authors also reported that from the 1960s to the 1990s, differences in actual cheating remained relatively stable across men and women. This suggests that while males may perceive cheating more positively, the actual rates of cheating across male and female populations is more similar.

In a subsequent article, Whitley (2001) argued that cheating behaviors of men and women are becoming more parallel. While women held more unfavorable attitudes towards cheating, actual cheating rates appeared consistent across both genders (Whitley, 2001). In addition, despite their findings of higher cheating among male students, McCabe and Trevino (1997) echoed this sentiment, arguing that the nature of this relationship remains inconclusive. These inconsistent results may be attributed to changes in the socialization of women in the United States.

Socialization Experiences of Female Students

Prior research has posited that cheating behaviors are an outcome of the distinct socialization experiences of men and women. (McCabe & Trevino, 1997; McCabe et al., 2012; Ward & Beck, 1990). For females, these experiences often encourage conformity towards societal rules, thus explaining their lower rates of academic misconduct (McCabe & Trevino, 1997; McCabe et al., 2012; Ward & Beck, 1990). In contrast, the socialization experiences of males may be less stringent, therefore encouraging a higher incidence of cheating among men

(Ward & Beck, 1990). This view of value development was analyzed further by other early researchers.

In a study by Byers and Powers (1997), ethical perspectives among college students were examined. More precisely, the researchers explored how value orientations were different among male and female students. Upon analysis, this study yielded surprising results concerning gender and moral attitudes. Initially, Byers and Powers (1997) hypothesized that females would display more idealistic views than males. For this study, idealism was characterized as a student's belief that positive outcomes can be achieved through legitimate means. Furthermore, Byers and Powers (1997) believed that more female students would subscribe to this train of thought. However, contrary findings were derived from the data. Overall, male students displayed higher levels of idealism when compared to female students. Despite these unexpected results, these perceptions could be driven by the historic marginalization of women in society. For females, achieving academic and professional goals may have proven more challenging given societal circumstances. As such, one could surmise that fewer female students believed that success could be achieved through legitimate measures.

Relatedly, Tibbetts (1999) inquired about morality levels between male and female students. Within the context of academic dishonesty, females appeared more impacted by unethical behaviors. Specifically, anticipated levels of shame for cheating was higher among female participants, which was possibly influenced by their unique socialization experiences (Tibbetts, 1999). Gibson and colleagues (2008) later corroborated this argument for heightened morality among female college students. The data utilized by Gibson et al. (2008) were collected one decade prior to publication, thus falling around the same time period as the research by Tibbetts (1999). As such, anticipation of guilt could possibly explain prior disparities in cheating across male and female students. Despite these findings, McCabe and colleagues (2012) argue

that the marginal differences in gender cheating appear to be diminishing. This could be an outcome of shifting trends in female socialization.

Changing Gender Trends

According to McCabe and his team (2012), previous gender distinctions are no longer applicable among modern college populations. In previous decades, the socialization of females was quite distinct from that experienced by males (McCabe et al., 2012). However, representation of women in both higher education and the workforce has increased considerably (Ma et al., 2016; Mann & DiPrete, 2013). Consequently, current observations would suggest that female students have adopted more similar behaviors to male students (McCabe et al., 2012). This is particularly true within discussions of collegiate academic dishonesty. Modern research has implied that the gap between male and female cheating appears to be narrowing (Beasley, 2016; Martin et al., 2009; McCabe et al., 2012). This may further suggest that sociological influences once discouraging women from cheating may be less relevant among current institutions. For example, greater opportunities now exist for women within the labor market (Mann & DiPrete, 2013). Similarly, enrollment trends in higher education reveal a larger inclusion of female students.

For most of history, females have represented the minority of enrolled college students. However, recent decades have seen significant changes in this demographic. Since 1991, female enrollment in higher education has exceeded male student registration (Ma et al., 2016). These increases in female student attendance also have impacted specific fields of study. In certain areas, women have been steadily occupying majors that have been historically male-dominated (Mann & DiPrete, 2013). Female participation within STEM (Science, Technology, Engineering, and Mathematics) is an excellent example of such changes. Since the 1970’s, a growing number of females have majored in studies within the STEM discipline. In 1977, women accounted for

only 5% of the total engineering majors in the United States (Mann & DiPrete, 2013). By 2002, this proportion of female engineering students had risen to 21% (Mann & DiPrete, 2013). While women are still disproportionately represented in the STEM field, the increase in female participation is promising. Experiencing similar stressors may also lead to an equitable rate of cheating between men and women. In fact, when controlling for academic major in contemporary research, men and women generally behave similarly with respects to academic dishonesty (Lambert & Hogan, 2004; McCabe et al., 2001; McCabe et al., 2012).

In the broader scope of cheating rates between genders, the research evidence remains inconsistent. In a recent national sample of college students, self-reported cheating rates were higher among male students (Yu et al., 2017). However, in a study by Martin and associates (2009), unique findings were reported concerning gender and plagiarism. These researchers initially hypothesized that no statistically significant differences would be observed between male and female students. Contrary to what the researchers expected, female students displayed higher involvement in plagiarism behaviors than male students. As such, further exploration of gender's influence on cheating is necessary. In particular, further research could examine how gender might interact with other explanatory variables.

Interactions with Other Variables

Within the context of academic dishonesty, researchers have argued that male students are more likely to engage in cheating than female students (Bowers, 1964; Davis et al., 1992; McCabe & Trevino, 1997; Pino & Smith, 2003; Tibbetts & Myers, 1999; Whitley et al., 1999). Examination of the gender compositions within international cohorts may prove relevant to further academic dishonesty research. While some previous research examined cultural drivers for foreign student behavior, Beasley (2016) posited that gender may mediate the relationship between nationality and academic dishonesty. In Beasley's (2016) study, females represented the

larger proportion of the domestic student population. However, for non-domestic students, the proportions were reversed, indicating a much greater presence of males in international cohorts. As such, the demographic attributes of international students may be the stronger explanation for disparities in formal cheating incidents (Beasley, 2016). Additionally, the previous findings of gender distinctions in cheating may influence instructor attitudes and actions. In believing that male students engage in higher rates of academic dishonesty, instructors may feel more comfortable in reporting international male students for their behavior.

Within the context of academic major, researchers also have examined how gender potentially interacts with this variable. Specifically, a person's gender may moderate the relationship between academic major and academic dishonesty. In certain studies, gender differences among criminal justice majors have been explored through quantitative analysis. While several studies have examined this potential interaction, statistically significant findings were not achieved (Tibbetts, 1998; Lambert & Hogan, 2004). To illustrate, in examining criminal justice and non-criminal justice majors, Tibbetts (1998) also investigated potential gender disparities in academic misconduct. While Tibbetts (1998) found certain distinctions between criminal justice and non-criminal justice majors, the gender variable proved insignificant. Men and women, regardless of their academic major, displayed similar intentions to cheat. Any differences that were observed among these groups failed to reach a statistical significance.

In a later study, Lambert & Hogan (2004) found statistically significant findings that males engaged in more academic dishonesty than females, and this gender effect remained stable across criminal justice and non-criminal justice majors. More precisely, male criminal justice majors and male non-majors displayed higher rates of cheating than their female counterparts. In contrast, McCabe and colleagues (2012) later assessed the relationship between these variables,

finding that males and females display similar cheating behaviors when controlling for academic major. Their findings indicated men and women who belong to the same academic major will exhibit parallel inclinations for academic misconduct (McCabe et al., 2012).

Relatedly, academic major and gender may interact within the context of ethical perceptions. In one study, Byers and Powers (1997) examined the ethical orientations of male and female criminal justice students. Specifically, the authors investigated major differences between these different groups of students. Among their findings, Byers and Powers (1997) reported an interesting result concerning male criminal justice students, whereby male criminal justice students possessed a more unified perspective towards ethics. Furthermore, many male criminal justice students believed that positive outcomes could be achieved through legitimate means, as evidenced by the higher levels of idealism among the male participants (Byers & Powers, 1997).

In contrast, the results among female criminal justice students were far more varied. On measures of idealism, for example, the responses from women showed a wider dispersion (Byers & Powers, 1997). Even among the male and female non-majors, greater dispersion was observed in participant responses. This may suggest an interaction effect between gender and academic major in influencing ethical development. In addition, gendered differences in moral behaviors may also apply to criminal justice professionals. Several researchers have determined the presence of behavioral inequalities between male criminal justice professionals and female criminal justice professionals (Bjerregaard & Lord, 2004; Alley et al., 1996). In partial contrast to Byers and Powers (1997) findings, the likelihood of unethical behaviors among female professionals was less pronounced.

Age

Research concerning age and academic dishonesty has been fairly consistent, indicating that younger college students are more prone to academic misconduct (Haines et al., 1986; Lambert & Hogan, 2004; McCabe & Trevino, 1999; McCabe et al., 2012). In general, this age disparity may be a reflection of maturity and educational background (Beasley, 2016). Younger college students appear less proficient in academic practices, making them more likely to engage in course misconduct (Beasley, 2016). By comparison, older college students possess more maturity, which could explain their lower incidence of academic dishonesty (Haines et al., 1986; Lambert & Hogan, 2004). Increased maturity also would explain the lower rate of a cheating among married students (Haines et al., 1986; Lambert & Hogan, 2004). Since married students tend to be older than the average college student, they may display more responsible behaviors within coursework.

Academic Rank

Another common concern within cheating research is whether age is an appropriate variable for analysis. More specifically, researchers have proposed that academic rank would be a more precise explanation for academic dishonesty among college students (McCabe et al., 2012). In Lanier's (2006) study, class rank was statistically significant in predicting cheating behaviors among students in traditional courses. However, the age variable only approached statistical significance, with a p-value of .098 (Lanier, 2006). This would suggest that age and academic class are not synonymous variables with each other. Rather, they have notable differences within the analysis of academic misconduct. Situational factors may also explain the differences between age and class rank. For example, underclassmen are often enrolled in larger general education courses. In these courses, cheating may seem more appealing to uninterested students (McCabe et al., 2012). As upperclassmen enroll in major specific classes, their interest

in course material may improve, decreasing the likelihood for academic misconduct (McCabe et al., 2012).

Online Students

Student age may be particularly important for cheating behaviors within online courses. Research has posited that academic dishonesty is less prevalent within online learning (Harmon et al., 2010; Stuber-McEwen et al., 2009; Tolman, 2017; Watson & Sottile, 2010). According to Stuber-McEwen and colleagues (2009), age can mediate the relationship between course type and academic dishonesty. In their study, Stuber-McEwen et al. (2009) examined behaviors among students enrolled in both traditional courses and online courses, while recognizing that the characteristics of online college students may be quite distinct from traditional students. For example, online students are typically older and have personal responsibilities, such as families and employment (Seaman et al., 2018; Stuber-McEwen et al., 2009). Stuber-McEwen and her team (2009) observed this trend within their sample of online students.

In Lanier’s (2006) study, age was a statistically significant variable in predicting academic dishonesty within online courses. In traditional courses, age failed to achieve significant results in explaining student cheating behaviors. This is a noteworthy finding for online courses. Lower cheating rates among online students would suggest a superior effectiveness in remote learning. However, online courses typically are comprised of older, non-traditional students. With greater inclusion of younger college students, online courses could exhibit an increased level of cheating. This is especially pertinent for students attending college during the Covid-19 pandemic. During the Covid-19 pandemic, a large proportion of undergraduate students have enrolled in blended or online learning. With this increased enrollment, new conclusions may be derived concerning cheating within remote courses.

Academic Achievement

In examinations of grade point average and academic dishonesty, findings have remained stable, showing that a negative relationship exists between these two variables. In general, researchers have found that cheating behaviors are widely observed among students with lower grade point averages (McCabe et al., 2012; McCabe & Trevino, 1997; Olafson et al., 2013; Pino & Smith, 2003; Roig & Caso, 2005). When controlling for course type, this relationship remains consistent among college students. Within online classes, the likelihood of academic dishonesty was significantly higher among students with lower academic averages (Lanier, 2006).

Student Pressure

The influence of grade point average on student cheating likely is driven by a variety of factors. First, college students may experience heavy pressure from family members and employers to excel academically (McCabe et al., 1999; McCabe et al., 2012). When students are unable to achieve these goals legitimately, they may turn to cheating as a resolution. For many students, cheating is necessitated as college completion otherwise would be unattainable (McCabe et al., 2012). Additionally, financial pressures among students may also contribute to academic misconduct.

For students on academic scholarship, certain grade point averages are often mandated for continued funding (McCabe et al., 2012; Stuber-McEwen et al., 2009). The fear of losing financial sponsorship may strongly impact students with lower grade point averages, making them more likely to engage in this form of misconduct (Stuber-McEwen et al., 2009). Grade requirements also apply to college athletes as well (McCabe et al., 2012). For student athletes, certain grades are required for participation on a team. In response to this pressure, athletes may engage in academic dishonesty. Overall, pressure to succeed academically can make cheating more appealing to students with lower grade point averages. However, students with higher

grade point averages may also engage in cheating as a reaction to personal pressure. For instance, certain students are driven by competition and seek to academically outperform other classmates. In this situation, a student with reasonably strong academic achievement may still engage in academic dishonesty (McCabe et al., 2012).

Varied Effects on Cheating

Research also has determined that academic achievement can have stronger influences on specific forms of cheating. In Roig and Caso's (2005) study, three specific measures of misconduct were analyzed: fraudulent excuses, cheating, and plagiarism. The researchers determined that grade point average had a negative relationship with all three of these factors. However, not all of these measures achieved statistical significance. While a student's grade point average proved significant in fraudulent excuses and cheating, a relationship with plagiarism could not be substantiated. A student's academic record can also impact student disciplinary hearings. More precisely, a student's grade point average can have a pronounced influence on university sanctioning (Larwood & Rankin, 2010). When undergoing formal hearings concerning alleged academic dishonesty, students with lower academic achievement appear to have a higher incidence of guilty verdicts (Larwood & Rankin, 2010).

International Students

International students represent an important population for colleges. In recent years, the United States has hosted a growing number of international students within American institutions (Simpson, 2016). In 2016, the United States attracted over one million international students (Seaman et al., 2018). For many universities, the revenue generated by international enrollment is quite appealing (Cantwell, 2019; Hegarty, 2014). Specifically, this revenue can be especially vital to the financial stability of an institution (Hegarty, 2014). Furthermore, international student enrollment can have implications for the greater economy (Hegarty, 2014). According to Hegarty

(2014), collegiate enrollment by foreign students generates $22 billion dollars for the United States each year. Unlike domestic students, tuition generated by international students is often seen as more profitable among university administrators (Cantwell, 2019). As such, a dramatic loss in the international student population could impact the financial health of the United States.

According to Cantwell (2019), institutional profitability depends on certain thresholds being achieved in international student enrollment. Specifically, certain institutions may not observe desired profitability if international enrollment remains low. As such, higher emphasis on international recruitment can be beneficial to an institution. Furthermore, to maintain competitive advantage among other countries, American colleges need to adequately support these international students upon arrival in the country (Cantwell, 2019; Hegarty, 2014; Simpson, 2016). In the event that international students are inadequately supported by universities, this can have a detrimental impact on collegiate operations (Hegarty, 2014). These additional considerations for foreign students may be especially relevant to the issue of academic dishonesty (Simpson, 2016).

As previously stated, academic dishonesty is present across different student populations. However, students of international origins may face distinct challenges within the context of cheating. More precisely, international students can encounter greater issues concerning acceptable behaviors for coursework (Amsberry, 2010; Beasley, 2016; Bista, 2011). As a result, these students may unintentionally plagiarize within class assignments (Amsberry, 2010; Bamford & Sergiou, 2005; Beasley, 2016; Bista, 2011; Mundava & Chaudhuri, 2007). For foreign students, detection of plagiarism appears easier among instructors (Beasley, 2016; Mundava & Chaudhuri, 2007; Sacks, 2008). Differences in grammar and writing style may make it more apparent to an instructor that certain portions of writing are plagiarized (Beasley, 2016).

This may influence the number of formal cheating charges filed against international students at American institutions.

Generally speaking, the number of cheating incidents formally addressed by university administrators represents a small fraction of the perceived cheating rates among college students (Beasley, 2016; Happel & Jennings, 2008; McCabe et al., 2012). Previous research would suggest that instructors often prefer to handle cheating incidents informally, often making arrangements with the students directly (Beasley, 2016; McCabe et al., 2012). However, among the incidents that are formally addressed by institutions, international students appear to be disproportionately represented (Beasley, 2016; Bi, 2013; Sacks, 2008; Simpson, 2016). When compared against expected cheating rates, Beasley (2016) reports that international students are five times more likely to be formally reported. Relatedly, international students are more likely to be dismissed from an institution following a formal disciplinary process (Sacks, 2008). Based on this data, one could surmise that academic misconduct is more rampant among international student populations. However, making such generalizations about the international student population should be met with caution (Beasley, 2016; Mundava & Chaudhuri, 2007).

While international students may face more official university proceedings, this does not necessarily imply that academic misconduct is more prevalent among this population of students (Beasley, 2016; Mundava & Chaudhuri, 2007). Rather, it may simply suggest that international students are sanctioned more frequently. However, sanctioning a large group of international students for academic misconduct may prove detrimental to the long-term stability of higher education. As asserted by Gallant and colleagues (2015), developing preventative measures may prove more effective than punishments. This may be particularly true for international students. To respond to such issues, researchers have conducted studies to fully examine the circumstances of international students and to identify any key distinctions that distinguish them from domestic

students. A frequently cited topic concerning this issue is the cultural differences that exist among foreign students.

Cultural Differences

For international students studying in the United States, adapting to a new culture is a common challenge (Bista, 2011; Hayes & Introna, 2005; Mundava & Chaudhuri, 2007). In particular, acclimating to unfamiliar learning styles can be especially difficult for students of international origin. In general, learning styles and academic assessment are quite different in other countries (Amsberry, 2010; Bista, 2011; Hayes & Introna, 2005). For these students, past educational experiences may be different from those experienced in the United States. More precisely, other countries often place a greater emphasis on memorization of concepts and facts (Bista, 2011; Hayes & Introna, 2005). In one study, Bista (2011) determined that nearly 94% of international students reported memorization was the primary learning tool within prior education. This may contrast practices at American institutions, where students often engage in critical thinking activities and written expression.

For written assignments especially, college students generally need a certain familiarity with sentence structure and grammar. However, a large proportion of international students may lack proficiency in the English language (Amsberry, 2010; Bista, 2011). This limited language proficiency and inexperience with writing can compound the academic struggles of these students (Amsberry, 2010; Bista, 2011). At American universities, college students are often encouraged to develop their own unique writing style (Amsberry, 2010). For student assignments, the use of paraphrasing is often utilized within academic writing. Paraphrasing enables a writer to embody the principle arguments of past authors while also incorporating their own voice and writing style. However, this practice may be particularly concerning among international students. For these students, they may fear misinterpreting the concepts of an

author. In response, they may copy sentences directly as a way of avoiding such an error (Amsberry, 2010). In many scenarios, such challenges with acclimation may lead to a higher incidence of cheating behaviors (Amsberry, 2010; Bamford & Sergiou, 2005; Bista, 2011; Hayes & Introna, 2005; Simpson, 2016).

For international students, engagement in academic dishonesty may be a response to psychological challenges they endure due to cultural acclimation (Bista, 2011). As previously stated, adjusting to a new academic environment can be challenging for international students. However, beyond academic acclimation, foreign students must also adjust emotionally as a student in the United States. Specifically, international cohorts may experience psychological or social issues with moving to a new country (Bista, 2011; Jackson et al., 2013). For these students, coping with stressors, such as financial struggles, homesickness, and difficulty with socialization, may lead to more serious mental health issues (Bista, 2011; Jackson et al., 2013). As such, additional support services may be needed among international populations (Bista, 2011; Jackson et al., 2013).

While universities do offer support services to students, international students appear less likely to utilize such opportunities (Eisenberg et al., 2007; Jackson et al., 2013). According to Eisenberg and colleagues (2007), international students appear to have lower self-awareness concerning their need for help. Specifically, when compared to domestic students, they determined that foreign students felt uncomfortable seeking help during difficult situations (Eisenberg et al., 2007). However, university-sponsored support may be fundamental to these students. For international students, hesitancy to utilize such services may have implications on cheating behaviors. According to Bista (2011), engagement in academic misconduct becomes much more likely when international students are confronted with personal stressors. In response

to these emotional pressures, these students may turn to illegitimate conduct as a way of progressing academically (Bista, 2011).

Due to cultural differences, misunderstandings about defined cheating behaviors can arise among international cohorts. In general, domestic students may have a greater understanding of academic dishonesty and the actions that constitute cheating (Beasley, 2016; Bista, 2011; Hayes & Introna, 2005). Alternatively, international students may not have that same level of understanding for academic misconduct (Beasley, 2016; Bista, 2011; Hayes & Introna, 2005). In some instances, perceptions may widely deviate across these groups of students. In one study, roughly 50% of international students claimed to lack an understanding of academic policies within the American education system (Bista, 2011). For these students, comprehending the seriousness of plagiarism is a challenge.

It is worth noting that American perceptions towards academic plagiarism are not entirely shared by other countries (Amsberry, 2010; Bista, 2011; Mundava & Chaudhuri, 2007). Specifically, issues related to "textual ownership" can be particularly pronounced among international cohorts (Amsberry, 2010; Mundava & Chaudhuri, 2007). While verbatim copying of text is considered dishonest in the United States, other countries may perceive this as an acceptable behavior (Amsberry, 2010; Bista, 2011; Mundava & Chaudhuri, 2007; Simpson, 2016). In a study of disciplined college students, claims of ignorance was a commonly cited justification (Beasley, 2014). Students who were caught cheating claimed that they did not fully understand what constituted academic dishonesty. As such, foreign students may engage in these behaviors, unaware of the potential consequences. In sum, for international students, differences in academic culture can lead to unintentional cheating (Amsberry, 2010; Beasley, 2016; Bista, 2011).

While cultural adjustments are challenging for international students in the United States, other western countries experience similar issues with foreign cohorts. In general, the academic practices across western countries appear more similar than those found in other parts of the world. Yeh & Inose (2003) determined that students from European countries had easier transitions to American academic culture than those from other continents. These findings could also be tied to proficiency in English speaking among European students. Similar to the United States, students studying in the United Kingdom may encounter comparable challenges with academic dishonesty. Hayes & Introna (2005) compared the behaviors of British students against those who originated from foreign countries. Upon analysis, the researchers found key disparities across the two groups of students.

Whereas British students appeared to have more serious impressions of cheating behaviors, the foreign groups displayed widely contrasting viewpoints (Hayes & Introna, 2005). For instance, while 94% of British students considered copying another student's work as a serious issue, only 20% of Asian students shared the same opinion. This large disparity would suggest that other countries may regard certain academic practices more leniently. Relatedly, Bamford & Sergiou (2005) yielded similar findings in a cohort of international students, all of whom attended school in London. Upon review of the responses, roughly half of the students had admitted to previous acts of plagiarism. Moreover, many of these students cited previous cultural practices as the major driver for such behaviors. Within their findings, Bamford & Sergiou (2005) revealed that several international students regarded copied text as an acceptable practice in their countries of origin. Consequently, they carried this belief into studies at foreign institutions.

Cultural adjustment appears to be a major driver for the overrepresentation of international students in academic dishonesty cases (Beasley, 2016). However, adjustments to a

new academic culture cannot be defined as the singular explanation for cheating among this group of students (Amsberry, 2010). Rather, it is one of several factors that influence academic misconduct among international students. When examining the behaviors of international cohorts, it is also possible that other variables interact with citizenship, which is in need of further research.

Summary and Conclusions

The seriousness of academic dishonesty appears quite evident. Among college student populations, excessive cheating poses a serious threat to the quality and integrity of higher education. Therefore, a greater urgency in addressing this issue is recommended. In examining this issue, researchers often explore different factors that influence cheating likelihood among college students. Though studies have identified significant explanatory variables such as gender, age, international status, and grade point average, two variables are especially important within this research study: academic major and course type.

In previous studies, researchers have concluded that overall cheating rates among criminal justice majors are comparable to the general population of students (Eskridge & Ames, 1993; Lambert & Hogan, 2004). However, college student populations have changed considerably since these studies have been conducted. In analyzing this relationship within a modern educational context, differences were observed. Moreover, this research demonstrated that criminal justice students display distinct behaviors within certain contexts.

With respects to course type, researchers have investigated distinctions between traditional courses and online courses. Among these distinctions, academic dishonesty is an important concern that receives significant attention. Despite preconceived notions, previous studies concerning online student behaviors have often produced favorable results. Specifically, the observed incidence of cheating is typically lower among remote learners (Harmon et al.,

2010; Stuber-McEwen et al., 2009; Tolman, 2017; Watson & Sottile, 2010). These lower figures are often credited to the overrepresentation of non-traditional students within online courses (Harmon et al., 2010; Jaggars & Xu, 2010). However, prior conclusions may prove less pertinent within the current context of higher education. In response to the Covid-19 pandemic, most collegiate institutions have shifted to a remote learning structure.

For this most recent cohort of college students, learning was widely adapted around virtual instruction and online activities. As such, the demographics of the online student population have vastly changed in recent semesters. This educational shift may adjust previously reported trends of academic dishonesty. Moving forward, new research into modern student behaviors could prove especially useful to colleges. As discussed in the results, this study provided insightful findings concerning online students and criminal justice majors. Schools of criminal justice may benefit from these results within policy development.

CHAPTER THREE

Criminological Theories and Academic Dishonesty

Criminological theories often posit that individual decision-making can be explained through a variety of factors. More precisely, researchers often argue that such theories can serve as a framework for understanding criminal behavior. Over the years, theories such as social learning theory, deterrence theory, and rational choice theory have been commonly cited in criminal justice studies. Furthermore, prior research has determined that these criminological principles have utility in explaining academic dishonesty among college students (Freiburger et al., 2016; Hoeben & Thomas, 2019; McCabe et al., 2012; Nagin & Pogarsky, 2003). For college students, engagement in academic misconduct can be a deliberate decision based on various factors. Within the current study, several theoretical influences were explored for their ability to predict academic dishonesty in the contemporary higher educational environment.

This chapter first presents an overview of three relevant criminological theories to academic dishonesty research: social learning theory, deterrence theory, and rational choice theory. In general, principles from all three of these theories have explanatory power in the context of college student cheating. However, rational choice theory will serve as the central framework within this study. The second part of this chapter examines three rational choice components that are particularly relevant to the current research: likelihood of apprehension, likelihood of formal reporting, and peer influences. For likelihood of apprehension, the influence of instructor detection for cheating will be explored. Relatedly, a discussion on the likelihood of formal disciplinary reporting also will be presented. Lastly, the impact of peer relationships on student cheating is examined within this chapter.

Social Learning Theory

In studying human behavior, social learning theory is a widely researched model (Akers et al., 2017). In 1977, Ronald Akers introduced principles to further advance Edwin Sutherland's differential association theory. Like Sutherland, Akers (1977) posited that learning was a fundamental process to behavioral development. While social learning theory still embodied the major principles of its predecessor, Akers (1977) sought to expand on the overall process of learning. Through his theory, Aker's (1977) continued to argue that criminal offending was an outcome of learned behavior, but he further outlined his view of criminal learning as occurring through four major components: differential association, definitions, imitation, and differential reinforcement (Akers et al., 2017).

Differential association speaks to value orientations and how social interactions cultivate certain behaviors. According to Akers (1977), social interactions have an immense influence on learning and criminal activity. In both intimate and vicarious settings, individual associations can lead to favorable or unfavorable perceptions of illicit behaviors (Akers et al., 2017). Relatedly, definitions refer to the attitudes that people attribute to specific actions and behaviors. For certain individuals, positive interpretations of crime commission can promote offending. Alternatively, individuals with negative definitions of crime likely would refrain from such activities. For the imitation component, this involves modeling the behavior of others (Akers et al., 2017). In observing certain behaviors, an individual may mimic similar actions. Lastly, differential reinforcement reflects the anticipated costs and benefits of specific actions. According to Akers and colleagues (2017), these outcomes are social in nature and can illicit certain behavioral responses.

With respect to overall empirical support, social learning theory has produced favorable empirical findings. Shortly after publication of his theory, Akers and his colleagues (1979)

conducted their own empirical testing. This initial test yielded impressive results concerning the explanatory power of social learning principles on problematic behaviors among adolescents. Akers and colleagues (1979) determined that the four social learning components had a significant impact on student alcohol use and marijuana use, producing explained variation levels of 55% and 68% respectively. This would suggest that social learning variables are especially appropriate among student populations. In the following years, social learning variables would undergo substantial empirical testing concerning the efficacy of this theory (Akers et al., 2017).

In one meta-analysis, Pratt & Cullen (2000) examined 21 empirical studies and discussed how social learning theory contends with control theories. When compared against one another, control theories are often considered a competing explanation to social learning theory (Pratt & Cullen, 2000). As such, these two theories can be seen as mutually exclusive in the context of human behavior. In their review, however, Pratt & Cullen (2000) determined that social learning variables proved significant even in the presence of control variables. This body of research support for social learning theory would be further investigated in a subsequent meta-analysis by Pratt and colleagues (2010).

Compared to the earlier meta-analysis, Pratt and colleagues (2010) conducted a more extensive review dedicated to Akers' theory of social learning. In this research, 133 studies were identified and analyzed. In general, the meta-analysis again yielded favorable results for social learning theory. While the findings revealed strong support for all four components of the theory, the effects of differential association and definitions were distinct. Although each of the four tenets had a statistically significant relationship with individual behavior, Pratt et al. (2010) found the strongest evidence for differential association and definitions. In comparison, imitation and differential reinforcement yielded weaker statistical effects than the other two factors.

Moreover, the findings from this meta-analysis are consistent with research results specific to academic dishonesty.

In the context of academic dishonesty, social learning theory has served as an underlying framework for several studies. The relationship between social learning theory and academic misconduct was first posited among early academic misconduct studies (Bowers, 1964; McCabe & Trevino, 1997; McCabe et al., 2012). Specifically, these studies identified peer approval as a significant determinant in college student cheating. In situations where academic misconduct is a widely rejected behavior, college students are less likely to engage in such behaviors (Bowers, 1964; McCabe & Trevino, 1997). Furthermore, principles of differential association may be particularly relevant in analyzing these peer relationships (McCabe et al., 2012). Through interactions with dishonest classmates, students can develop favorable justifications for cheating (McCabe et al., 2012). This also relates to principles of differential reinforcement. For students, observing successful cheating among peers can make such behaviors more appealing (McCabe et al., 2012). More precisely, cheating may be considered a learned behavior through these peer interactions (McCabe et al., 2012). Over time, research would further investigate this impact of peer influences on student cheating behaviors.

Deterrence Theory

Principles of deterrence have been widely influential in the policies and research of criminal justice. From a historical standpoint, deterrence theory derives from Cesare Beccaria (1963 [1764]) and his publication of *On Crimes and Punishments*. During this period, the criminal justice system was widely characterized by excessive brutality and unjust policies. For Beccaria (1963 [1764]), the overreliance on retributive justice was particularly troubling. However, it was his belief that human behavior was a rational response to situations and opportunities. Through this starting assumption, he reevaluated the use of punishment within

society, asserting that crime control could be achieved through policies that target human rationality and free-will. At the core of Beccaria's (1963 [1764]) arguments was this belief that crime prevention was superior to crime punishment. Specifically, he asserted that the threat of punishment could discourage criminal offending. To further outline his theory, he identified three central components: celerity of punishment, severity of punishment, and certainty of punishment.

The celerity component of deterrence refers to the swiftness of punishment following a criminal act. In minimizing the time elapse between a criminal offense and formal sanctioning, individuals may come to associate punishment as the expected outcome of crime. Among the three components of deterrence, celerity of punishment has received minimal attention within criminal justice research (Pratt & Turanovic, 2018). Although the principle appears logical, observing celerity effects on criminal offending appears quite difficult, as the criminal justice system is inherently delayed in criminal processing, making immediate punishments to offenders unattainable (Pratt & Turanovic, 2018). As such, the criminal justice system appears limited in reducing crime rates through use of swift punishments (Walters & Morgan, 2019). Among the research studies that have examined celerity, minimal support for the deterrent effect of swift punishments has been derived (Pratt & Turanovic, 2018).

Within higher education, minimal research has been conducted on the effects of swift punishments on student behavior. In one study, Nagin and Pogarsky (2001) examined how the three deterrence principles impact drunk driving among college students. While certainty and severity of punishment produced significant effects on deviant behavior, a celerity of punishment effect was not observed. Similar to the criminal justice system, this may derive from delays in formal punishment. For university officials, the formal processing of disciplinary incidents is not an immediate endeavor. In cases of academic dishonesty, students can encounter delays between

their initial engagement in cheating and their formal punishment. For certain undergraduates, particularly present-focused individuals, the thought of future consequences may be given little consideration (Nagin & Pogarsky, 2003). As such, immediate satisfaction from cheating may outweigh the punishments potentially imposed sometime in the future. Overall, this would suggest that celerity of punishment has a weak influence on both criminal offending and college student behaviors. In comparison to celerity, the severity and certainty of punishment have received more research attention.

For offenders, severity of punishment references the harshness of imposed sanctions. More precisely, in fear of severe punishment, a potential offender would be deterred from crime commission. Over the years, deterrence studies have paid particular attention to the severity component (Nagin, 2013). Specifically, severity-inspired initiatives have been favored widely throughout the criminal justice system (Pratt, 2018; Tonry, 2018). This is illustrated by various notable policies, such as mandatory prison sentences and the death penalty (Nagin, 2013). Interestingly, Beccaria (1963 [1764]) fiercely opposed the overemphasis of severity in crime control policies. In his view, such measures would mirror the excessive harshness he had witnessed within society. In analyzing modern deterrence research, the findings would support Beccaria's (1963 [1764]) initial concerns.

Existing empirical findings generally suggest that initiatives centered on severe punishments fail to reduce criminal activity (Nagin, 2013; Pratt, 2010; Tonry, 2018). Furthermore, the effect of severity appears inferior to certainty of punishment (Nagin, 2013). Furthermore, these findings hold true for deterrence among college students. Using deterrence principles, researchers initially hypothesized that severe sanctions potentially could promote academic integrity among students. For many institutions, academic dishonesty is considered a serious offense and can result in a host of severe punishments. However, research has determined

that severe sanctions yield minimal influences in deterring such behaviors (Freiburger et al., 2017; Nagin & Pogarsky, 2003; Tibbetts & Myers, 1999). In contrast, practices related to certainty of punishment appear more successful within the field of academic integrity (Freiburger et al., 2017; Walters & Morgan, 2019).

Certainty of punishment refers to the likelihood of sanctions following a criminal offense. According to Beccaria (1963 [1764]), certainty of punishment was especially important within deterrence theory. To observe a deterrent effect among the general population, crimes had to result in punishment. In the absence of punishment, crime would be incentivized among prospective offenders. By building awareness of criminal sanctioning, illicit behaviors could be discouraged among such individuals. In speaking to this component, certainty of punishment has received the greatest empirical support within the criminal justice system, in comparison severity and celerity (Nagin, 2017; Nagin, 2018; Pratt, 2010; Tonry, 2018). Overall, increasing the likelihood of punishment produces significant effects on behavior (Pratt, 2010; Tonry, 2018).

Rational Choice Theory

Although social learning and deterrence theories have explanatory value within academic dishonesty research, rational choice theory was the most appropriate theoretical framework for this study. For this analysis, three major influences were examined within the context of college student cheating: likelihood of apprehension, likelihood of formal reporting, and peer influences. Likelihood of apprehension is a subtle divergent from certainty of punishment. For deterrence theory, fear of punishment is the central concept that guides this framework. However, certainty of apprehension seems to be a more appropriate characterization of the deterrent effect (Nagin, 2018). Specifically, offenders appear more influenced by the threat of apprehension than by subsequent sanctions (Nagin, 2018). For academic dishonesty research, this principle may also relate to the perceived likelihood of formal reporting. Likelihood of formal reporting may share

some commonalities with severity of punishment; however, the low rate of formal referrals by instructors likely influences behavior. While students may consider the likelihood of instructor detection in decision-making, a low perceived risk for formal reporting may promote cheating engagement. Lastly, peer influences are an important variable within academic dishonesty research (McCabe & Trevino, 1997). Peer relationships can promote the incidence of cheating among college students. While these factors can be argued from a deterrence and social learning standpoint, placement within rational choice theory was most suitable this examination of college student cheating.

Principles of Rational Choice Theory

Similar to deterrence theory, rational choice theory is centered on the principle of human rationality. Specifically, human behaviors are purposeful and reflect rational decision making on the part of an individual (Clarke & Cornish, 2001). The research of Cornish and Clarke (1986) has been especially prominent within criminological research. According to these researchers, individual actions often reflect careful consideration of perceived costs and benefits. In the context of criminal activity, offenders seek certain benefits through crime commission. In situations where the benefits of crime outweigh the potential costs, offending is more likely to occur (Cornish & Clarke, 1986). This is a key addition beyond the basic principles of deterrence. Whereas deterrence focuses on threat of punishment, rational choice theory emphasizes perceived gains and losses in criminal offending.

Prior to its conception, rational choice theory was influenced deeply by the environmental research of Ronald Clarke (1967; 1980). In his earlier research, Ronald Clarke argued situational context played an important role in illegal activities. Specifically, certain environments present individuals with heightened opportunities for illicit behaviors (Cornish & Clarke, 1985). In his view, altering physical spaces can lead to reductions in crime (Clarke,

1980). More specifically, when physical structures make crime more easily detected, prospective offenders will perceive offending as inopportune. As such, rational choice principles often guide programs in situational crime prevention (Newman & Clarke, 2016).

Situational crime prevention has a considerable influence on the criminal justice system. In particular, crime prevention strategies often address issues concerning environmental conditions that promote offending (Sidebottom & Wortley, 2016). Over time, situational crime prevention has been adapted into a variety of criminal justice initiatives. For instance, increased street lighting is a notable preventive measure for crime, and research has found support for improved street lighting in reducing neighborhood crime rates (Davies & Farrington, 2020; Farrington & Welsh, 2002; Welsh & Farrington, 2008).

As increased lighting creates greater visibility on certain streets, heightened awareness and perceived detection of crime often is associated (Davies & Farrington, 2020). For a rational individual, crime in a lighted area may appear costlier, thus discouraging prospective offenders (Davies & Farrington, 2020). Among college students, instructors have adopted similar measures to increase the visibility of cheating. Like for criminal offenders, this heightened risk of detection can make academic misconduct a weaker investment for students. As such, the risk of apprehension appears to have significant utility in studies of crime and academic dishonesty.

Likelihood of Apprehension

As previously discussed, researchers have argued that the likelihood of apprehension has a greater influence on human behavior than the certainty of punishment (Nagin, 2013; 2018). When discussing this principle, rational choice theory is an appropriate theoretical framework. Although apprehension can be viewed as a deterrence principle, research has found that individuals often conduct a cost-benefit analysis where risk of detection is deliberated (Clarke & Cornish, 1985; Horney & Marshall, 1992). Furthermore, situational factors may influence

individual reasoning and decision-making (Cornish & Clarke, 1986). For prospective offenders, avoiding criminal detection is preferred (Clarke & Cornish, 1985; Nagin, 2015). When identifying a target, offenders favor situations where escape is easier after a crime commission (Felson, 1995). In principle, crime reduction should be observed when individuals are at greater risk for apprehension. Relatedly, likelihood of apprehension is a key consideration for academic dishonesty research.

Empirical research suggests that student cheating rates are influenced by the risk of detection (Freiburger et al., 2017; Nagin & Pogarsky, 2003; Walters & Morgan, 2019). More precisely, when the prospect of instructor detection is higher, students are less likely to commit academic dishonesty. In an early study, Nagin and Pogarsky (2003) found cheating incidents were lower among college students when risk of detection was heightened. Furthermore, this effect was more pronounced than the threat of school sanctions. Research also has determined that cheating is often a repeat offense among college students (Sideridis et al., 2015). Repeat offenses often surface when individuals have prior success in illicit actions (Clarke & Cornish, 2001). For offenders, these previous successes can lead to a false sense of confidence in subsequent crimes (Horney & Marshall, 1992; Paternoster et al., 1983). For college students, prior success in cheating may lead to greater confidence in cheating. As such, detection and rational choice are more suitable concepts for cheating analyses. In more current studies, researchers have echoed this sentiment, presenting statistically significant support for the likelihood of detection (Freiburger et al., 2016; Walters & Morgan, 2019).

For college instructors, adjusting classroom environments can have a significant impact on student behaviors. In general, instructors can enact certain strategies that inflate the risk of detection for student cheating. To illustrate, Hodgkinson et al. (2016) presented several situational strategies as a means to reduce cheating behaviors among college students. Their

recommendations included increased surveillance by test proctors and the use of plagiarism software. Both of these techniques focus on enhancing the risk of detection, which could reduce academic dishonesty rates.

The use of proctors during examinations is a highly cited strategy among researchers. Specifically, this strategy is easily adoptable and proves effective in reducing cheating rates (Coston & Jenks, 1998; Freiburger et al., 2017; Sideridis et al., 2015). However, the mere presence of a proctor during an examination may be inadequate in discouraging cheating. For instructor surveillance to have a maximum effect, students must be closely monitored and seats must be appropriately distanced (Hodgkinson et al., 2016). In practice, enacting preventative measures is a superior strategy to university sanctioning (Hodgkinson et al., 2016). However, strategies for online courses may require more creativity. Use of anti-cheating software in classes may prove especially necessary for instructors. Furthermore, use of these resources may have implications on the likelihood of formal reporting.

Likelihood of Formal Reporting

Prior research generally suggests that the threat of severe punishments has a limited impact on student cheating behaviors (Nagin, 2013; Nagin & Pogarsky, 2003; Pratt, 2010; Tonry, 2018). However, these findings may reflect the low perceived likelihood of formal reporting for cheating. In general, the vast majority of academic misconduct incidents are unreported by university instructors (Freiburger et al., 2016; Happel & Jennings, 2008; McCabe et al., 2012; Staats et al., 2009). In a sample of students across two universities, roughly 70% reported past cheating behaviors (Freiburger et al., 2017). In contrast, only 5% of the student sample reported being formally processed for academic misconduct. In general, other studies have echoed these findings. Within the college student population, roughly 1 to 2% face formal disciplinary hearings for cheating behaviors (Happel & Jennings, 2008; Davis et al., 2009;

Vanderpool & Cates, 2013). For college students, this low perceived likelihood of formal disciplinary referral may influence cheating behaviors. In the absence of widespread disciplinary action, students may perceive cheating as a low risk activity. With such low rates of imposed punishments (Freiburger et al., 2016), students may feel encouraged to cheat. However, the recent rise in online learning and digital software may have an influence on the likelihood of formal reporting.

For many faculty, there is a widespread belief that academic dishonesty is more prevalent in online courses. For this reason, many instructors deem online instruction as an inferior system for learning (Harmon et al., 2010; Stuber-McEwen et al., 2009). Despite these preconceptions, research has suggested that cheating behaviors are less prevalent among online students (Harmon et al., 2010; Stuber-McEwen et al., 2009; Tolman, 2017; Watson & Sottile, 2010). These lower rates may be attributed to cheating prevention software employed by online instructors.

For instance, a concern among online instructors is the lack of supervision during online exams. However, remote proctoring software such as Respondus Lockdown Browser (RLB) appears to be a suitable alternative to in-person proctors (Stack, 2015). In an experiment involving online criminal justice students, participants took an examination in two distinct environments: on-campus with a proctor and online via the Respondus program (Stack, 2015). Upon analysis of the test scores, no statistically significant differences were reported. This contrasted with prior research findings where online students in an unproctored environment typically scored higher than proctored students (Stack, 2015). These results may suggest that the Respondus Lockdown Browser creates comparable test environments to traditional courses. In response, students may refrain from cheating just as they would in a physical proctored classroom. Moreover, Respondus may generate digital evidence of student cheating, which could heighten the risk for formal referral. In essence, this proctoring software could reduce concerns

of academic dishonesty in unsupervised online settings (Stack, 2015). Moreover, this software may influence student perceptions concerning the risk of formal disciplinary referral for cheating.

Similarly, with regard to plagiarism, Turnitin® is a widely popular program among college instructors (Bruton & Childers, 2016). Through this software, instructors can identify plagiarized elements of student submissions. Specifically, "cut and paste" plagiarism is quite common among college students (McCabe et al., 2012). However, these portions can be easily identified within Turnitin®. This may also have implications on the likelihood of formal disciplinary action. When deliberating formal referral for cheating, a key hesitation among instructors is lack of evidence (Staats et al., 2009). However, anti-cheating software may increase an instructor's confidence that academic dishonesty has occurred. With these generated similarity reports as evidence, college instructors may feel more inclined to formally report incidents of cheating. As such, engaging in such behaviors may prove riskier to students, making them hesitant to cheat.

Despite these successes, certain limitations still exist for both of these anti-cheating programs. For Respondus Lockdown Browser, test cheating can still surface among remote learners. While the Respondus program may block certain web-browser actions while taking an online exam, students can still consult with other classmates or reference printed notes (Stack, 2015). However, with webcam activation working in concert with the lockout browser, this may become less of an issue. For Turnitin®, the limitations appear more instructor-oriented. Although most faculty approve of Turnitin®, a small proportion of faculty voice concerns regarding this software (Bruton & Childers, 2016). Among these concerns are issues with intellectual property and lack of faculty cohesion in using the software (Bruton & Childers, 2016). For this reason, faculty may be hesitant in Turnitin® usage within college courses.

Nonetheless, initiatives that focus on the increased likelihood of detection and formal reporting may prove effective in reducing cheating rates among traditional and online students.

Peer Influences

In the decision-making process, student behaviors are widely impacted by peer influences (De Buck & Pauwels, 2019; Osgood et al., 1996; Thomas & McGloin, 2013). While peer relationships are commonly examined within social learning theory, studies also suggest that such influences have applicability within a rational choice framework. For rational choice theory, a core characteristic is the weighing of prospective costs and benefits for certain actions. While adolescents may simply mimic the delinquent behaviors of their fellow youth, thought processes and internal deliberation still occur (Osgood et al., 1996). More specifically, these individuals still engage in a cost-benefit analysis prior to criminal or delinquent acts. However, these decisions also appear more short-sighted (Osgood et al., 1996).

In the presence of peers, the potential consequences may appear marginal to the immediate benefits derived from deviant behavior (Osgood et al., 1996). In general, adolescents may not be inherently deviant (De Bucks & Pauwel, 2019; Thomas & McGloin, 2013). Rather, deviant behaviors may be a response to specific external experiences. Peer pressure can be quite compelling, and for many youth, this can lead to behaviors and actions that would otherwise seem unappealing (De Buck & Pauwels, 2019). In unstructured settings, especially, this effect can be more pronounced (De Buck & Pauwels, 2019). Relating this to a rational choice framework, the benefits of illicit activities may be social in nature. For students who desire peer acceptance, delinquent acts may appear as a rational conduit to goal obtainment. In addition to adolescent delinquency, peer influences may also impact college student engagement in academic dishonesty. This effect is particularly noteworthy among criminal justice majors.

For criminal justice programs, examining the impact of peer influences on student behaviors can be significant. As previously reviewed, overall rates of cheating between criminal justice majors and non-majors are generally equitable, suggesting a stability across the entire college student population (Eskridge & Ames, 1993; Lambert & Hogan, 2004; Tibbetts, 1998). Furthermore, researchers have found few behavioral distinctions among criminal justice students. However, studies have noted peer interactions having a unique impression among these students (Lambert & Hogan, 2004; Tibbetts, 1998). In the context of academic dishonesty, peer influences seem to have an amplified effect on cheating likelihood among students majoring in criminal justice (Lambert & Hogan, 2004; Tibbetts, 1998). From a rational choice perspective, this may imply that criminal justice majors recognize an added social benefit to cheating that is otherwise absent from other academic majors. Similar to adolescents, college students may engage in cheating behaviors as a means of social acceptance among classmates. Alternatively, academic dishonesty may stem from mimicking the behaviors of classmates.

According to Freiburger and colleagues (2017), observing cheating among other students can influence an individual's decision to engage in similar acts. This is particularly true when incidents of academic dishonesty go widely unpunished by the instructor. Interestingly, the mere presence of peers can impact individual decision-making (Hoeben & Thomas, 2019). When multiple people are gathered in large settings, isolated behaviors become less apparent (Hoeben & Thomas, 2019). As such, individuals may perceive lower detection odds when they behave illicitly in large groups (Hoeben & Thomas, 2019). This is quite applicable among college student populations. In large lecture halls, being surrounded by classmates may reduce the perceived risk of detection by an instructor. In these scenarios, a student may display greater confidence in cheating than if they belonged to a small lecture group. With regard to classroom

structure, the complete absence of a shared learning space may be relevant in academic dishonesty research.

In the online learning environment, remote learners are often disconnected, both physically and personally, from instructors and peers (Sun & Chen, 2016). For this reason, the dynamics of student relationships may be quite different than in traditional courses. In general, the cooperation between online classmates may be limited. This disconnect may weaken the traditional effect of peer influences on academic dishonesty. Moreover, students may display more independent decision-making within an online course, being uninfluenced by other student behaviors. As criminal justice majors are the most widely effected by peer behaviors, further investigation into this line of inquiry is warranted.

The Current Study

In sum, academic dishonesty has been a widespread issue across collegiate institutions (McCabe et al., 2012). While academic dishonesty may be viewed by some as a marginal concern, these behaviors pose a serious threat to higher education. High rates of academic dishonesty among a student body reflects poorly on the educational quality and legitimacy of an institution. Furthermore, failure to address student cheating may lead to a public distrust of higher education (Bernardi et al., 2008; Keith-Spiegel et al., 1998). In addition to institutional factors, academic dishonesty may produce long-term challenges for students, as engagement in unethical behaviors is rarely limited to a student's college experience. Following graduation, students often continue unethical behaviors well into adulthood (Sims, 1993). As such, techniques to reduce these academic dishonesty rates should be explored.

Previously, important and insightful research studies on collegiate cheating have been performed. However, contemporary changes in higher education delivery warranted new exploration into this topic. The worldwide Covid-19 pandemic also has had a significant impact

on the delivery of education. Prior to this pandemic, online students represented a fraction of enrolled learners. Since 2020, enrollment statistics have shifted drastically, with many universities adopting more of an online learning model (“Our List of College Reopening”, 2020). As such, prior findings concerning student cheating behaviors do not adequately reflect modern cohorts of college students.

A goal of this current study was to examine how patterns in academic dishonesty may have changed with the rather dramatic change in online enrollments. Furthermore, this study examined behaviors specific to criminal justice majors and identified distinctions among this group of students. To fully investigate these inquiries, use of rational choice theory as the underlying framework was especially valuable. In quantitative research studies, theoretical perspectives often ground the research, with variables being constructed to reflect these principles. In using components related to rational choice theory, current behaviors constituting academic dishonesty were explored and further explained. This study hypothesized that the likelihood of detection, the likelihood of formal reporting, and peer influences would each have an influence on student decisions to cheat. It was also hypothesized that enrollment in online courses may further compound this issue when compared against traditional courses. Through survey creation, data collection, and various forms of statistical analysis, rational choice principles and various individual level factors served as the central explanatory variables in investigating contemporary academic misconduct.

CHAPTER FOUR

METHODOLOGY

The purpose of this study was to examine academic dishonesty among students at a mid-sized university in the New England region. Specifically, this study addressed two central inquiries during analysis. First, distinct behaviors among criminal justice and non-criminal justice students were explored through statistical testing. While past research suggests overall rates of cheating appear stable across criminal justice and non-criminal justice students, behavioral distinctions have been reported among the former. Most notably, peer influences appear more prominent among criminal justice majors (Lambert & Hogan, 2004; Tibbetts, 1999). As such, data concerning peer influences was collected for this research project. Second, cheating within online and traditional course settings also was assessed. Specifically, this study examined how academic dishonesty varies between traditional courses and online courses.

This chapter describes the design and methodology for this study. First, the central research questions and hypotheses are provided. In developing these questions and hypotheses, previous research findings were referenced. Second, the data collection process is discussed, with specific details concerning sampling being provided. Next, the independent and dependent variables within this study are presented and the coding for each of these variables is outlined.

Research Questions & Hypotheses

Academic dishonesty among criminal justice students and within online courses has been assessed in several studies (Coston & Jenks, 1998; Eskridge & Ames, 1993; Harmon et al., 2010; Lambert & Hogan, 2004; Lanier, 2006; Tibbetts, 1998; Watson & Sottile, 2010). However, limited research exists on the intersectionality of these two variables.

Principles of rational choice theory served as the underlying framework for this study. In particular, components such as likelihood of detection and peer influences were incorporated into the following research questions:

1. What variables influence the likelihood of academic dishonesty among college students?
2. Does rational choice theory help explain the potential relationship between likelihood of cheating detection and academic dishonesty?
3. Does rational choice theory help explain the potential relationship between likelihood of formal referral and academic dishonesty?
4. Does rational choice theory help explain the potential relationship between peer influences and academic dishonesty?

While these research questions have been examined in previous literature, the current timing of data collection is quite relevant. Prior research has suggested that academic dishonesty is less prevalent in online courses than in traditional courses (Harmon et al., 2010; Stuber-McEwen et al., 2009; Tolman, 2017; Watson & Sottile, 2010). However, these findings may prove less relevant within the current educational environment. Modern higher education has been widely impacted by the worldwide Covid-19 pandemic. In response, many colleges have shifted toward the online delivery of education. As such, the demographics of online students have changed dramatically in the past year. Previously, online enrollment was typically dominated by older and non-traditional students (Seaman et al., 2018; Stuber-McEwen et al., 2009). However, with colleges embracing remote course delivery, a more diverse group of students have enrolled in online learning. This highlights a major research distinction within this study. The shift to greater use of online learning was sudden, and this study analyzed academic dishonesty in the context of the recent pandemic. As such, this study considered how this new educational environment impacted student perceptions towards cheating detection and the

influence of peer behaviors on cheating. These research findings should inform policy decisions at the institutional level and among criminal justice faculty. To further investigate the scope of these research questions, several specific hypotheses were created.

H_1: For all students, academic dishonesty will be more likely in online courses than in traditional courses.

To date, higher education has shifted towards an online platform of educational delivery. However, a major reservation among professors is the perceived increase in cheating within online courses (Harmon et al., 2010; Rowe, 2004). In general, previous research has suggested that academic dishonesty is less prevalent in online courses than in traditional courses. However, this lower incidence of cheating is often explained by the demographics of remote learners. Online courses typically appealed to older and non-traditional students. As determined by prior studies, academic dishonesty appeared less prevalent among older students (McCabe et al., 2012). However, the Covid-19 pandemic has changed the composition of online courses. While older students more typically enrolled as distance learners, a much larger proportion of younger students have participated in online learning recently. This is in direct response to the circumstances surrounding the current pandemic. With this shift in the online student demographic, previous conclusions concerning cheating in remote courses seem less relevant. The wide inclusion of younger students will likely influence modern measures of online academic dishonesty. Given the current situation, it was suspected that students enrolled in online courses will display a higher likelihood of cheating than those enrolled in traditional courses. This served as a central inquiry within this study.

H_2: For online and traditional coursework, criminal justice majors will exhibit a lower likelihood of academic misconduct than non-criminal justice majors.

Another central inquiry within this dissertation was how academic major influenced academic misconduct in online and traditional courses. To examine this hypothesis, statistical modeling for cheating behaviors by criminal justice and non-criminal justice students was utilized. In addition, consideration was given to whether criminal justice majors reported a lower likelihood of cheating than non-criminal justice majors in online courses, traditional courses, or both. This investigation was guided by interest in the curriculum and objectives of the criminal justice discipline. As a student, criminal justice majors potentially are exposed to more ethics training than other academic majors (Coston & Jenks, 1998; Tibbetts, 1998). Having this additional ethics training may influence a student's perception of unacceptable behaviors. Furthermore, criminal justice majors enter professions where high moral standards are required (Coston & Jenks, 1998; Eriksson & McGee, 2015; Eskridge & Ames, 1993; Tibbetts, 1998). As such, logic would dictate that criminal justice majors would display lower levels of cheating than the general population of college students.

While previous studies have shown little or no statistical differences between criminal justice majors and non-criminal justice majors (Eskridge & Ames, 1993; Lambert & Hogan 2004; Tibbetts, 1998), this dissertation tested this hypothesis within a modern academic environment. More specifically, the current study hypothesized that modern-day criminal justice majors would engage in lower levels of cheating behaviors. This position was derived for several reasons. First, the previous studies examining cheating behaviors among criminal justice students are dated. The landscape of higher education and the criminal justice discipline have evolved substantially over the past few decades. For example, ethics training has become more central to

the criminal justice curriculum (Dioguardi, 2016). Conducting this test in a modern educational setting did yield contrasting results to previous research.

H_3: For all students, academic dishonesty will be greater when perceived likelihood of instructor detection is low.

Previous research has posited that likelihood of detection can impact certain human behaviors (Nagin 2013; 2018). Within criminal justice, offenders often favor situations where criminal detection can go unnoticed (Clarke & Cornish, 1986; Nagin, 2015). Similarly, college students appear to employ a similar mindset when engaging in academic dishonesty, as studies have revealed that college students are more likely to cheat in situations where instructor detection is lower (Freiburger et al., 2017; Nagin & Pogarsky, 2003; Walters & Morgan, 2019). In situations where likelihood of detection were higher, reductions in cheating were observed (Nagin & Pogarsky, 2003). Consistent with previous literature, this current study expected similar results among survey respondents. When the perceived likelihood of detection appears low, survey respondents should have reported a higher willingness to cheat.

H_4: For all students, academic dishonesty will be greater when perceived likelihood of formal disciplinary action is low.

Relatedly, an influence of formal referral on cheating behaviors was also expected. In general, empirical research has found weaker support for severe punishments in discouraging academic dishonesty (Freiburger et al., 2017; Nagin & Pogarsky, 2003; Tibbetts & Myers, 1999). Overall, more severe sanctions appear to produce minimal influences on college cheating behaviors. However, these findings may be a byproduct of contextual factors across institutions.

Among colleges, formal reporting for academic dishonesty remains relatively low (Freiburger et al., 2017; Happel & Jennings, 2008; McCabe et al., 2012; Staats et al., 2009). While self-reported data suggest that cheating is common among college students, only a small

proportion of students are formally disciplined for such behaviors. Consequently, this likely impacts student attitudes towards academic dishonesty. With few cheating incidents being officially sanctioned, students may perceive cheating as a low risk activity. This perception may further compound the issue of widespread academic misconduct on college campuses.

Nonetheless, this current study hypothesized that recent cohorts of college students will be more widely impacted by the likelihood of formal processing. For many instructors, lack of evidence is often a key hesitation when deliberating official referrals for student cheating (Staats et al., 2009). However, this pandemic has led many institutions to rely heavily on digital software and technology. Through anti-cheating software, instructors could more easily identify incidents of academic dishonesty. In turn, this may have led to higher confidence levels among instructors, thus a higher rate of formal reporting. As such, students should have displayed more caution in the current technological learning environment.

$H_{5:1}$: For criminal justice majors, peer relationships will have a greater influence on the likelihood of academic misconduct than for non-criminal justice majors.

$H_{5:2}$: For online courses, peer relationships will have a lesser influence on the likelihood of academic misconduct than in traditional courses.

As previously stated, the role of peer influences on academic dishonesty was another line of inquiry within this research study. Prior research has found that students appear widely impacted by peer behaviors (De Buck & Pauwels, 2019; Osgood et al., 1996; Thomas & McGloin, 2013). In the context of academic dishonesty, students may engage in cheating after witnessing or hearing about similar actions among peers (Freiburger et al., 2017). When looking at criminal justice majors specifically, these effects were especially pronounced (Lambert & Hogan, 2004; Tibbetts, 1998). In previous studies, criminal justice majors appeared especially susceptible to peer influences (Lambert & Hogan, 2004; Tibbetts, 1998). Consistent with

previous research findings, this study expected a similar result among modern criminal justice students.

In addition, peer influences were expected to have a distinct influence among distance learners. In the online environment, learning experiences are quite different from traditional courses. Specifically, remote learners often are disconnected from their fellow peers (Sun & Chen, 2016). With this limited interaction, it was believed that peer influences would be less relevant within online courses. In the absence of frequent communication with classmates, students should display more independent decision-making in the context of academic dishonesty. As such, the impact of peers on online course cheating was believed to be minimal.

$H_{6:1}$: For online and traditional coursework, younger students will exhibit a higher likelihood of academic misconduct.

$H_{6:2}$: For online and traditional coursework, the likelihood of academic dishonesty will be similar across all genders.

$H_{6:3}$: For online and traditional coursework, students with lower grade point averages (GPA) will exhibit a higher likelihood of academic dishonesty.

$H_{6:4}$: For online and traditional coursework, international students will exhibit a higher likelihood of academic dishonesty.

For this study, demographic variables were collected for student participants. Characteristics such as age, gender, grade point average (GPA), and citizenship were reported and measured. During analysis, the impact of each of these independent variables on academic dishonesty were explored. Furthermore, interaction effects between these demographic variables and other independent variables were examined in statistical testing.

For age, previous research has reported fairly consistent results concerning academic dishonesty among different age groups. Specifically, the relationship between age and academic

misconduct appears negative (Haines et al., 1986; Lambert & Hogan, 2004; McCabe & Trevino, 1999; McCabe et al., 2012). As student age increases, participation in cheating appears to decrease. Based on previous findings, similar results were expected in this study.

Gender differences in cheating have been widely explored by researchers. Overall, previous research has investigated differences between males and females, yielding inconclusive findings. In prior studies, socialization distinctions among female students often were used as an explanation for any observed discrepancies in cheating rates (McCabe et al., 2012). However, current trends in higher education suggest that women are becoming more represented in institutional enrollment and historically male-dominated majors (Ma et al., 2016; Mann & DiPrete, 2013). With higher proportions of female and non-binary students represented in higher education, a goal of this study was to produce greater understanding about cheating behaviors between different gender groups. Specifically, this study hypothesized that cheating behaviors would be relatively similar across gender groups.

The research concerning grade point average and cheating likelihood was also fairly consistent. In general, the relationship between grade point average and academic dishonesty appears negative (McCabe et al., 2012; McCabe & Trevino, 1997; Olafson et al., 2013; Pino & Smith, 2003; Roig & Caso, 2005). For students with higher GPAs, the likelihood of cheating is lower. As such, this study hypothesized that students with lower GPA's would express higher likelihoods for academic dishonesty.

Differences between domestic students and international students was also analyzed. In the distributed survey, students were asked about their citizenship status at the university. Prior research suggests that international students are disproportionately represented in formal cheating proceedings (Beasley, 2016; Bi, 2013; Sacks, 2008; Simpson, 2016). Specifically, cultural differences have made academic dishonesty more prevalent among international students

(Bista, 2011; Hayes & Introna, 2005). For these students, greater issues with completing academic assignments had led to a higher rate of cheating incidents (Amsberry, 2010; Bista, 2011). However, it is worth noting that many of these incidents appear unintentional in nature (Amsberry, 2010; Beasley, 2016; Bista, 2011). The current study did not imply that international students are more prone to dishonest behaviors, but the analysis did consider whether international students report a higher likelihood of academic misconduct.

Data Collection

For this study, primary data was collected for analysis. The research was conducted at a four-year private university in the New England region of the United States. The institution had a combined undergraduate and graduate population of nearly 6,900 students. In terms of enrollment breakdown, roughly 4,900 were undergraduate students and 1,900 were graduate students. For the 2020/2021 academic year, the university offered three main types of courses: traditional classroom, hybrid courses, and online courses. However, educational delivery shifted more towards online delivery. Academically, the university offers nearly 100 undergraduate degrees and 50 graduate degrees. These degree programs are split among five schools: Arts & Sciences, Engineering, Business, Health Sciences, and Criminal Justice & Forensic Sciences. For this institution, criminal justice majors represent a large proportion of the campus community. As such, this institution was particularly well suited for an analysis of cheating behaviors among criminal justice majors.

Survey of Students

As discussed in the research objectives, this study identified key factors that influence academic dishonesty among criminal justice and non-criminal justice students, in both online and traditional coursework. In analyzing academic dishonesty among college students, collecting self-reported data was suitable. As previously stated, self-reported incidents of cheating vastly

surpass the rate of formally reported incidents (Freiburger et al., 2017). In using official institutional data, the rate of academic misconduct may be widely underrepresented. As such, collecting data from students through use of a survey was a logical method for this research project. According to Bachman and colleagues (2017), surveys have several attractive features for researchers. First, surveys are considered quite versatile, as they can collect data on a multitude of topics. Second, surveys are considered an efficient option for data collection, as cost and timeliness can be minimized. Lastly, surveys can generate data from a large population or sample of individuals, aiding in the generalizability of findings. All three of these features made survey use an appealing tool for this study. Additionally, survey use offered certain advantages for quantitative analysis. Descriptive statistics, associations between variables, and the predictive potential of independent variables on dependent variables can be derived through statistical modeling (Creswell & Creswell, 2018).

Sampling Strategies

While this study intended to collect responses through a survey instrument, various survey distribution plans were considered. In general, samples can be produced through probability and non-probability methods, such as random, convenience, quota, and snowball sampling (Bachman et al., 2017). Each sampling technique offers certain advantages to researchers. As such, it is important to identify a suitable sampling technique that aligns with the objectives of a specific study. For this research study, maximizing the overall response rate was desired. To identify an appropriate sampling technique that accomplished this goal, previous research studies and institutional limitations were considered.

For past studies, use of convenience sampling techniques were popular. Convenience sampling is a non-probability technique in which participants are selected on the basis of availability. Convenience sampling is especially common among university professors (Bachman

et al., 2017). For faculty, distribution of surveys to college students in classrooms is relatively easy. Relatedly, accessibility was a strong consideration in this study, as all student participants will derive from one institution. In previous studies of academic dishonesty, use of convenience sampling often yielded high response rates (Lambert & Hogan, 2004; Lanier, 2006; Walters & Morgan, 2019).

In other cases, for universities with larger student populations, a stratified random sampling approach was utilized. In these studies, researchers randomly selected courses and requested permission from instructors for survey distribution during their respective class periods (Freiburger et al., 2016; Vowell & Chen, 2004). Under normal circumstances, an in-person stratified random sample would have been possible for this study. Specifically, paper surveys would have been distributed in specific classes. The courses would be selected through stratified random sampling, and the respective instructors contacted for permission to distribute the survey. This method likely would yield a high student response rate and be more representative of the campus community. However, with the emphasis on online learning, limited in-person class-time, and restrictions on classroom capacity and face-to-face interactions, an online distribution appeared most appropriate.

For this study, the survey was distributed campus-wide, to all currently enrolled students in the spring 2021 semester. Following IRB approval, a link to the online survey was emailed to 6,898 undergraduate and graduate students. In general, online distribution of surveys can be a less desirable method for research studies. Specifically, online surveys often yield low response rates (Dillman, 2014). Low response rates, combined with a smaller student population, can produce a weaker research methodology. To a certain extent, however, these weaknesses were mitigated. In order to encourage higher response rates among the student body, financial incentives were utilized. Students who complete the online survey were entered into a random

drawing for gift-cards. Twenty gift-cards ($10 each; $200 total) were available to students who completed the online survey. Shortly after closure of the survey, winners of drawing were emailed a gift-card for their participation.

Additionally, a series of follow-up emails were sent to students during the survey period. These emails served as a reminder to students and encouraged them to participate in the study. Overall, these combined methods did appear to positively impact survey responses. In addition, issues traditionally associated with online surveys were less prevalent in this study. According to Dillman (2014), online surveys can suffer from issues of internet access. More specifically, potential participants may not have internet access or high-speed internet capabilities (Dillman, 2014). However, with the institutional emphasis on online learning, this did not pose an issue among previously enrolled students at the university.

When collecting survey data, sample size is a key consideration among researchers. When reporting the results of a study, greater generalizability can be derived from a larger sample. As this study examined one moderately-sized institution, the results may not reflect behaviors of other college students in the United States. Nonetheless, a certain response rate was desirable for this population of nearly 6,900 college students. Isreal (1992) discussed appropriate sample sizes for a research study, with precision levels or measures of sampling error in mind. For a population of 7,000, Isreal (1992) recommended a sample size of 378, associated with a precision level of ± 5%. However, participation of 959 individuals could reduce the precision level to ± 3%. In general, minimizing sampling error can yield findings that more closely resemble the population. As such, for this study, the minimum response rate needed to satisfy Isreal's (1992) guidelines was 6%. However, generating closer to 959 responses required about a 14% participation rate among the 6,900 students. In this study, a participation rate of nearly 16% (1,084 responses) was achieved. As such, this study exceeded the initial goal for a 14%

response rate. This comparatively high response rate can be attributed to the financial incentives offered and the series of reminder emails sent to the student body.

Human Subject Issues

In developing this study's methodology, concerns for human subject issues were considered. First, the issue of age was addressed during survey distribution. While college students are typically over the age of 18, certain underage students may have received invitations to this survey during online distribution. To avoid concerns over parental consent, students under the age of 18 were directed to abstain from this survey. If an underage student attempted the survey, an alert was triggered when they input their age, instructing them to discontinue from participation.

For eligible students, the point of voluntary participation was stressed in the initial university email and within the survey. Students were assured that the survey was not mandatory and did not fulfill requirements for the university. Students were instructed that non-completion of the survey would signify voluntary "withdrawal" from the study. These surveys were then omitted from data entry and analysis. Furthermore, the potential risks to human subjects were minimal. Students should not have experienced adverse effects to their physical or emotional state in completing this academic dishonesty survey.

In terms of participant responses, measures to ensure anonymity were enacted. Within the survey, no identifying information was requested, nor did students have an opportunity to input comments. Since this study was centered on academic dishonesty among college students, reassuring each participant of response privacy was crucial to data collection. While characteristics such as age, gender, and citizenship were measured, the linking of individual survey responses to specific students did not occur. Following survey closure, the collected data was available only to the principal investigators. To potentially receive the financial incentive,

students needed to fully complete the survey. Once completed, students were directed to a separate survey where they could enter their email address. From this list of emails, twenty students were chosen randomly and directly contacted with a gift-card link. Creating a separate link for these emails further ensured anonymity among the student participants.

Survey Platform & Randomization

For data collection, Google Forms was utilized for survey creation. Google Forms was utilized because it was cost effective, offered creative survey features, and was capable of aggregating the data into SPSS for analysis. A central inquiry within this research was whether course type influenced academic dishonesty, and whether course type serves as a moderator for other variables. To fully investigate the likelihood of cheating within different class environments, random assignment was integrated into survey distribution. Using an online link randomizer, participants were randomly assigned into a treatment or control group. For the treatment group, students were asked questions that focused on academic dishonesty within an online course setting. Alternatively, members of the control group were presented with similar questions that involve a traditional classroom context. Random assignment into different groups is an effective strategy for assessing moderation effects. Using this design, in statistical analysis, split models were produced based on class type and academic major, and predictors of academic dishonesty were compared (Clogg et al., 1995; Paternoster et al., 1998). This was done to investigate whether the effects of various independent variables might be significantly different between the online and traditional class setting and between criminal justice and non-criminal justice majors.

Instrumentation

In designing the survey, completion time was taken into account. For online distribution, survey time becomes a more relevant factor in response rates. To illustrate, in a survey of

students attending the University of Michigan, the researchers reported that students generally discontinued the web survey around the 9-minute mark (Crawford et al., 2001). As such, the survey was designed so that it could be completed within 10 minutes. This likely encouraged a higher rate of survey submissions.

Timeline & Approval Process

Once a formal research design and methodology was established, expedited approval from the IRB was pursued. A request was made for a campus-wide email distribution of the survey. Upon approval, the data collection process began, and the survey was dispersed to both undergraduate and graduate students. With respect to timeline, the survey was emailed to students on April 20th, 2021, and it closed on May 4th, 2021. During this two week period, students were sent several reminder emails that encouraged them to complete the survey. Upon survey closure, 1,084 student responses were submitted. These responses then were downloaded into SPSS for statistical analysis.

Variables

Control Variables

In the survey, participants were asked a series of demographic questions. For these demographic variables, students reported their age, educational status, school information, gender, grade point average, and citizenship. These variables served as control variables in this study. The questions and coding for these variables are presented in Table 1.

Table 1

Control Variables

Variable (SPSS Coding)	Questions and Coding
Age (*age*)	What is your age in years?
Graduate Status (*status*)	Are you an undergraduate student or a graduate student? 0 = undergraduate student 1 = graduate student
Academic School (*school*)	In which of the following five colleges does your major (or intended major) belong? 0 = Criminal Justice & Forensic Sciences 1 = Arts & Sciences 2 = Business 3 = Engineering 4 = Health Sciences
Gender (*gender*)	What is your gender? 0 = male 1 = female 2 = non-binary choice
Grade Point Average (*GPA*)	What is your estimated grade point average (GPA)? 0 = less than 2.0 1 = 2.00 – 2.49 2 = 2.50 – 2.99 3 = 3.00 – 3.49 4 = 3.50 – 4.00
Student Citizenship (*citizenship*)	Are you an international student? 0 = no, a domestic student 1 = yes, an international student

Independent Variables

One primary purpose for this research was to explore differences between criminal justice majors and non-criminal justice majors. In this study, academic major served as an independent variable, and students reported whether or not they were a criminal justice major. Additionally, this study investigated whether student behaviors differ between online and traditional course settings. Major and course type also were used in split modeling during statistical analysis, to assess moderation effects. With this in mind, students were directed randomly to one of two surveys involving questions related to different course types.

In these surveys, students were presented with one of two vignettes. The first vignette corresponded to student behaviors in traditional courses. These respondents served as the control group, and they were presented with the following scenario:

> Suppose you are a student in a fully on-ground college course. Your class meets between 2:20 and 3:35 p.m. every Tuesday and Thursday afternoon, and you are expected to attend class regularly. Your instructor teaches in-person lectures each week. Three exams are scheduled during the semester. These multiple-choice exams are distributed by your instructor and taken in-class during your 2:20 – 3:35 p.m. class period. Other assignments, including homework and a written paper, are submitted in hardcopy to your professor in-class throughout the semester.

Alternatively, respondents in the treatment group received a vignette related to an online learning experience. These respondents were presented with the following scenario:

> Suppose you are a student in a fully online asynchronous college course. Your class has no assigned class time, but you are expected to regularly complete your coursework online. Your instructor posts video lectures online each week. Three exams are scheduled during the semester. These multiple-choice exams are taken and submitted online. Digital

copies of your homework and a written paper are uploaded online throughout the semester.

In response to these scenarios, participants were asked a series of questions related to academic misconduct. Specifically, they reported their perceived likelihood of detection, likelihood of formal referral for test cheating, perceptions of cheating costs, and their likelihood for cheating in these situations. For this study, the underlying theoretical framework was rational choice theory. Prior research suggested that principles of rational choice theory may provide explanatory guidance for the likelihood of college student cheating. As such, three questions related to perceptions of cheating costs were included. These questions asked students to report how costly cheating was to their academic success, peer relationships, and familial relationships. Furthermore, peer influences, likelihood of detection, and likelihood of formal reporting are especially noteworthy within the context of academic dishonesty. As such, a series of questions related to these components were included in the survey. In addition, a question related to the perceived quality of education received was included. For students assigned to the online course survey, three additional questions were added. These questions assessed previous use of anti-cheating software within an online course. Overall, the questions were formatted as both dichotomous and continuous measures, as shown in Table 2.

Table 2

Independent Variables

Independent Variable	Questions and Coding
Academic Major (*major*)	Are you a criminal justice major? 0 = no, not a criminal justice major 1 = yes, a criminal justice major
Course Type (*course_type*)	This variable was produced based on which survey a participant completed. The surveys were randomized and distinguished based on the vignettes students received. 0 = traditional class vignette 1 = online class vignette
peer_exams	In this type of class, have you personally witnessed a college classmate cheat on an exam? Measured as a dichotomous variable. 0 = no 1 = yes
peer_homework	In this type of class, have you personally witnessed a college classmate work with others on a homework assignment when a teacher does not allow it? Measured as a dichotomous variable. 0 = no 1 = yes
peer_plagiarize	In this type of class, have you personally witnessed a college classmate plagiarize an assignment? Measured as a dichotomous variable. 0 = no 1 = yes

Independent Variable	Questions and Coding
detection_testcheat	In this type of class, estimate the likelihood of a cheating student being caught for test cheating by an instructor. 0 = 0% likelihood 10 = 100% likelihood
detection_plagiarism	In this type of class, estimate the likelihood of a cheating student being caught for plagiarism by an instructor. 0 = 0% likelihood 10 = 100% likelihood
detection_homework	In this type of class, estimate the likelihood of a cheating student being caught for homework cheating by an instructor. 0 = 0% likelihood 10 = 100% likelihood
reporting_testcheat	In this type of class, estimate the likelihood of a cheating student being formally referred to the Dean of Students for a test cheating violation. 0 = 0% likelihood 10 = 100% likelihood
reporting_plagiarism	In this type of class, estimate the likelihood of a cheating student being formally referred to the Dean of Students for a plagiarism violation. 0 = 0% likelihood 10 = 100% likelihood
reporting_homework	In this type of class, estimate the likelihood of a cheating student being formally referred to the Dean of Students for a homework violation. 0 = 0% likelihood 10 = 100% likelihood

Independent Variable	Questions and Coding
costs_academic	In this type of class, would you consider cheating to be more costly or more beneficial to your academic success? 0 = more costly 10 = more beneficial
costs_peer	In this type of class, would you consider cheating to be more costly or more beneficial to your peer relationships? 0 = more costly 10 = more beneficial
costs_familial	In this type of class, would you consider cheating to be more costly or more beneficial to your familial relationships? 0 = more costly 10 = more beneficial
quality_perceptions	In this type of class, how would you rate the typical quality of instruction provided? 0 = very poor 10 = excellent
webcam *(online course only)*	In this type of class, how often do professors require use of a webcam when taking an exam? 0 = never 10 = always
respondus *(online course only)*	In this type of class, how often do professors use the Respondus Lockdown Browser when taking an exam? 0 = never 10 = always

Independent Variable	Questions and Coding
turnitin *(online course only)*	In this type of class, how often do professors use Turnitin® for papers and other written assignments? 0 = never 10 = always

For this study, the influence of peers, the likelihood of detection, and the likelihood of formal referral were investigated. These independent variables capture different dimensions of peer influences and cheating detection, both of which are relevant to the theoretical framework. Furthermore, measures concerning the perceived costs and benefits of cheating were included. These variables embody the cost/benefit analysis commonly associated with rational choice theory. In addition to the independent variables listed above, several composite measures were created for peer influences, overall detection, overall reporting, and overall perceptions of costs & benefits. The composite measures are listed in Table 3 below. After being assessed for their internal reliability (Aldrich, 2018; Kremelberg, 2011; Lewis-Beck, 1995), these composite measures were utilized within various statistical models for this study.

Table 3

Independent Variable Composite Measures

Product Term	Summary and Coding
peer_influences	This is an overall additive measure of peer influences on academic dishonesty. A composite measure using the three independent variables related to peer influences. Expressed as a count value ranging from 0 – 3.
likelihood_detection	This is an overall measure of the likelihood of detection for academic dishonesty. A composite measure using the three independent variables related to detection by instructor. Calculated as an average of the three independent variables and expressed as a value ranging from 0 – 10.
likelihood_reporting	This is an overall measure of the likelihood of formal reporting to the Dean of Students for an academic integrity violation. A composite measure using the three independent variables related to formal reporting by an instructor. Calculated as an average of the three independent variables and expressed as a value ranging from 0 – 10.
costs_overall	This is an overall measure of the perceptions of cheating costs & benefits. A composite measure using the three independent variables related to perceptions of costs & benefits. Calculated as an average of the three independent variables and expressed as a value ranging from 0 – 10.

Dependent Variables

Measures of the likelihood of student academic dishonesty served as the dependent variables in this study. Identification and measurement of the likelihood of cheating were guided by the research of Bowers (1964) and McCabe and Trevino (1993). These researchers highlighted nine prominent forms of cheating among college students. From 1990 to 2010, McCabe and his colleagues also collected ongoing survey data concerning these measures of academic dishonesty (McCabe et al., 2012). Using this existing research, corresponding questions for these dependent variables were presented to students. Table 4 highlights the questions and the initial coding plan for responses.

Table 4

Dependent Variables

Variable	Questions and Coding
testcheat_copy	If you are enrolled in this type of class in the future, what is the likelihood of you copying from a classmate during a test? 0 = 0% likelihood 10 = 100% likelihood
testcheat_collusion	If you are enrolled in this type of class in the future, what is the likelihood of you giving answers to another student during an exam? 0 = 0% likelihood 10 = 100% likelihood
testcheat_advance	If you are enrolled in this type of class in the future, what is the likelihood of you receiving questions or answers from someone who has already taken the same exam? 0 = 0% likelihood 10 = 100% likelihood

Variable	Questions and Coding
testcheat_cribnotes	If you are enrolled in this type of class in the future, what is the likelihood of you utilizing notes during an exam when the teacher does not allow it? 0 = 0% likelihood 10 = 100% likelihood
homework_collusion	If you are enrolled in this type of class in the future, what is the likelihood of you working on an assignment with other students when the teacher does not allow it? 0 = 0% likelihood 10 = 100% likelihood
plagiarism_collusion	If you are enrolled in this type of class in the future, what is the likelihood of you turning in a paper done in part or entirely by someone else? 0 = 0% likelihood 10 = 100% likelihood
plagiarism_material	If you are enrolled in this type of class in the future, what is the likelihood of you plagiarizing from public material in a course paper? 0 = 0% likelihood 10 = 100% likelihood
plagiarism_padding	If you are enrolled in this type of class in the future, what is the likelihood of you adding citations to a bibliography you did not actually read in order to lengthen the reference list? 0 = 0% likelihood 10 = 100% likelihood

Variable	Questions and Coding
plagiarism_copy	If you are enrolled in this type of class in the future, what is the likelihood of you copying a few sentences of material without citing the source? 0 = 0% likelihood 10 = 100% likelihood

Upon analysis of these dependent variables, an overrepresentation of "0" responses was present for all these measures. While these dependent variables initially were designed as continuous variables, the lack of variation within responses posed a challenge to statistical analysis. In response, these dependent variables were recoded into dichotomous measures. In recoding, all "0" responses remained unchanged. These "0" responses indicate that a student had no likelihood of engaging in a specific cheating behavior. All other responses (1 – 9) were collapsed into a "1" group which indicated a possible likelihood for engagement within a respective behavior. While certain bivariate and multivariate models can use a dichotomous dependent variable, use of dependent variables with greater variation still was desired. Therefore, several composite scores were created using these nine dichotomous dependent variables. These composite measures, expressed as count variables, were intended to represent overall test cheating, overall plagiarism, and total cheating behaviors. For several multivariate analyses in this study, the composite dependent variables presented in Table 5 were utilized.

Table 5

Dependent Variable Composite Measures

Product Terms	Summary and Coding
testcheat_overall	This count variable is designed to represent the overall likelihood of test cheating behaviors among the participants. A composite measure using the four test cheating variables. Calculated as a sum of the four variables and expressed as a value ranging from 0 – 4
plagiarism_overall	This count variable is designed to represent the overall likelihood of plagiarism among the participants. A composite measure using the four plagiarism variables. Calculated as a sum of the four variables and expressed as a value ranging from 0 – 4
cheating_overall	This count variable is designed to represent the likelihood of all cheating behaviors among participants (test cheating, plagiarism, homework cheating). A composite measure using the nine cheating variables. Calculated as a sum of the nine variables and expressed as a value ranging from 0 – 9

Analysis Plan

Descriptive Analysis

Statistical analysis of the collected data began with a series of descriptive statistics. Specifically, frequency statistics were generated for each variable within this study. For researchers, descriptive statistics are used to organize data and summarize the characteristics for a collected sample (Aldrich, 2018; Kremelberg, 2011; Salkind & Frey, 2020). Through these measures, researchers can derive valuable insight concerning the collected data (Lewis-Beck, 1995).

This study included a range of control variables, independent variables, and dependent variables. Before conducting bivariate and multivariate analyses, the intention was to assess overall frequency distributions and report descriptive statistics for each of the included variables. The goal of this study was to garner a sample of students that adequately represented the entire campus community. For research studies, samples have greater generalizability when they are representative of an entire population (Lewis-Beck, 1995). In analyzing descriptive statistics, oversaturation by a specific group of students can be identified. As discussed in the results section, overrepresentation by GPA did occur within this study. Other than the GPA measure, the frequency distributions illustrate a better mix of students across other demographic categories. In general, assessment of these statistics offers researchers initial impressions of collected data (Lewis-Beck, 1995; Salkind & Frey, 2020). Although statistical significance could not be derived from frequencies alone, these analyses established a framework for deeper quantitative testing.

Bivariate Analysis

After producing the descriptive statistics, a series of bivariate statistics were calculated. Through use of bivariate analysis, researchers can explore the association between two variables

(Aldrich, 2018; Kremelberg, 2011; Lewis-Beck, 1995; Salkind & Frey, 2020). To initially explore possible relationships, various statistical tests can be performed. Among these tests, independent samples t-tests, analysis of variance, and Pearson correlation coefficients were generated.

Chi Square Analysis (Test of Independence)

Multiple chi-square analyses were conducted within this study. A chi-square analysis is a non-parametric statistic that examines the dispersion of frequencies within a body of data (Salkind & Frey, 2020). In general, chi-square statistics are appropriate for bivariate testing when the dependent variable is coded dichotomously. As discussed above, the nine recoded dependent variables satisfy this requirement. For chi-square testing, a comparison between expected frequencies and observed frequencies is conducted. In quantitative analysis, a chi-square test can be used to measure either one dimension or two dimensions (Salkind & Frey, 2020). For this study, multiple two-dimensional chi-square models were created. In the case of statistical significance, the chi-square statistic suggests that observed frequencies within the data deviated heavily from expected counts. In this study, a series of chi-square statistics were generated. As discussed in the results chapter, several of these chi-square statistics proved statistically significant.

Independent Samples T-Tests

In order to perform an independent samples t-test, the group means, the group sample sizes, and the sum of squares are calculated to produce a t-value (Kremelberg, 2011). The t-value is used to determine statistically significant differences between the two groups. Through statistical testing, the association between a single independent/control variable and a dependent variable can be observed. To run these models successfully, the dependent variable must be measured on a continuous scale (Aldrich, 2018; Kremelberg, 2011; Salkind & Frey, 2020). As

such, the nine dichotomous dependent variables would have proven inappropriate. For this reason, t-tests were utilized to highlight the differences between traditional students and online students. Specifically, several independent samples t-tests were generated to determine whether differences in cheating detection, cheating reporting, cost perceptions, and quality existed between traditional students and online students. For several of these variables, the differences between groups were statistically significant.

Analysis of Variance (ANOVA)

Similar to an independent samples t-test, an analysis of variance (ANOVA) examines differences between group means. However, use of an ANOVA allows for comparisons of more than two groups (Aldrich, 2018; Kremelberg, 2011; Salkind & Frey, 2020). This was particularly well suited for several of the independent variables in this study, such as school and grade point average. To perform an ANOVA, the variance between groups and the variance within groups are calculated in order to produce an F-statistic (Aldrich, 2018; Kremelberg, 2011; Salkind & Frey, 2020). Through computation of an F-value, researchers can identify statistically significant differences in mean values between groups. However, a statistically significant ANOVA model simply would suggest that a difference exists between groups (Salkind & Frey, 2020). Unfortunately, the nature of these differences cannot be derived from the ANOVA model alone. In cases where a statistically significant F-value is produced, further post hoc tests were performed to further identify the nature of these differences. Appropriate post-hoc tests were selected based on Levene’s test of equal variances. In cases where equal variances were not assumed, Tamhane’s post-hoc analyses were used in this study. Through use of a post hoc test, comparisons between groups are assessed, and researchers can successfully identify where the statistically significant mean differences appear (Aldrich, 2018; Kremelberg, 2011; Salkind &

Frey, 2020). This proved especially helpful during statistical analysis. Through use of post-hoc testing, differences among specific schools and GPA groups were identified.

Pearson Correlation Coefficients

After calculating various univariate and bivariate statistics, several Pearson correlation coefficients were generated. Through use of this statistic, the covariance between two continuously-measured variables are expressed (Kremelberg, 2011; Lewis-Beck, 1995). In general, a correlation coefficient can be used to measure the strength of an association between variables and the nature of a possible relationship. For example, a positive correlation coefficient would suggest a positive association between the two variables, whereas a negative correlation coefficient would suggest a negative or inverse relationship. For independent variables that were especially influential on academic dishonesty, a stronger correlation was observed through the test statistic and scatterplot of data points. In addition, these correlation coefficients were useful as a precursor to multivariate analysis. Correlation coefficients serve as a preliminary assessment of multicollinearity (Lewis-Beck, 1995; Lewis-Beck & Lewis-Beck, 2016). Lack of severe multicollinearity is one of the assumptions that must be met in utilizing multivariate regression techniques (Lewis-Beck, 1995; Lewis-Beck & Lewis-Beck, 2016). The correlation coefficients revealed that no two independent or control variables were highly correlated to one another within this study.

Multivariate Analysis

Following the bivariate analyses, a series of multivariate regression models were produced. Unlike the bivariate statistics that examine only two variables, multivariate analysis allowed for more than one independent variable in a statistical model (Lewis-Beck, 1995; Lewis-Beck & Lewis-Beck, 2016). When compared to bivariate analyses, multivariate testing is considered a stronger statistical tool within quantitative analysis (Kremelberg, 2011). In this

study, logistic regression and negative binomial regression were the primary multivariate models utilized.

Logistic Regression

Through logistic regression, the relationship between an independent and dichotomous dependent variable can be analyzed while also controlling for the effects of other variables (Menard, 2002). By including multiple variables in a single analysis, researchers also gain greater insight concerning the strength of predictor variables (Salkind & Frey, 2020). For this study, a logistic regression model was produced for each of the nine dichotomous cheating variables. Initial logistic regression models analyzed the relationship between demographic variables and each of the cheating dependent variables.

In subsequent models, perceptual variables were added to the regression analysis, and changes in significance were observed. In using this technique, researchers also can determine if the added variables contribute to the statistical significance and explained variation of a model. To determine explained variation, pseudo R-squared values were derived from these logistic regression models (Menard, 2002). The pseudo R-squared value is an estimate of explained variation between the independent variables and the dependent variable, therefore making a higher pseudo R-squared value desirable. During statistical analysis, multiple logistic regression models were created and analyzed using combinations of independent variables. As shown in the results chapter, several of the logistic regression models generated impressive pseudo R-squared values.

Negative Binomial Regression

As previously discussed, three cheating composite measures were created in order to conduct further multivariate regression analysis. Preliminary examination of these three composite measures identified an overrepresentation of zero cases within each of these

composite variables. In traditional linear regression testing, an overrepresentation of zero cases generally produces a violation of the normality assumption. In addition, there were relatively large variances across all three composite measures, indicating a positive skew. In situations where the variance for a dependent count variable is larger than the mean (referred to as over-dispersion), a negative binomial approach can be utilized (Kremelberg, 2011). Through use of a negative binomial regression, dependent variables are expressed in log counts instead of the original units. Using this approach resolves concerns with the normality assumption and other possible violations for linear regression models. For this study, a series of negative binomial regression models were produced. The first set of models analyzed the impact of various independent variables on each of the cheating composite measures. A subsequent set of models included the three software variables and analyzed cheating behaviors specific to online students. This approach of statistical testing also was utilized in split modeling for course type and academic major.

Following the estimation of full negative binomial regression models, comparisons between groups in two specific independent variables were analyzed. Specifically, the effects of independent variables within the two groups of the course type variable and within the academic major variable were compared against one another. Using statistical techniques outlined by Clogg et al. (1995) and Paternoster and colleagues (1998), comparisons between the regression coefficients were explored during this stage of multivariate analysis. This provided insight as to whether course type and major moderate the effects of the other independent and control variables.

To investigate potential moderating effects, the data were divided into two blocks using a data splitting technique in SPSS, which allowed for subgroups to be to be analyzed (Aldrich, 2018). First, responses were separated based on course type. Participants who answered

questions concerning the traditional course setting were separated from those who responded to online learning questions. Once separated, negative binomial regression models were created that reflect potential interactions between the independent variables in predicting the dependent variables within these two groupings (Clogg et al., 1995; Paternoster et al., 1998). In using this strategy, distinct impacts of certain independent variables on academic dishonesty were derived. Furthermore, a similar splitting analysis occurred for criminal justice majors and non-criminal justice majors. In splitting and assessing responses based on academic major, differences in independent and control variable effects between these student groups were assessed.

Summary

The purpose of this chapter was to outline the primary research questions and hypotheses investigated, along with the methodology and analytical strategies utilized in this study. As discussed, this study was concerned with the occurrence of academic dishonesty across different course settings and between criminal justice and non-criminal justice majors. To fully explore this issue, data were collected through use of an online student survey. Use of an online survey was especially useful for satisfying the objectives of this research.

Survey items were developed through use of previous literature and the core hypotheses being investigated in this research. The survey was distributed electronically to the student body at a moderately-sized university in New England. Efforts to maximize the response rate were enacted during data collection, and a sample of 1,084 responses was produced. Once collected, the data were subjected to a series of quantitative analyses that involved descriptive, bivariate, and multivariate statistical modeling. Each of these models highlight the relationships between variables and determine statistical support for each of the research hypotheses.

CHAPTER FIVE

Results

In order to fully investigate the issue of academic dishonesty among college students, a series of statistical analyses were conducted. Using the data collected from online survey distribution, the influence of various independent variables on cheating intentions were examined. This chapter presents three major forms of data analysis: descriptive, bivariate, and multivariate analysis.

For the descriptive analysis, frequency statistics were produced for each of the independent and dependent variables. These overall frequencies highlighted the variability in responses within this study. For the bivariate analysis, several models analyzed the relationship between specific independent variables and academic dishonesty intentions. The results of various chi-square tests, analyses of variance (ANOVA), and Pearson correlation coefficients are provided within this section. Lastly, several multivariate models are presented and discussed. The multivariate analyses incorporate multiple independent variables within each model. For this study, the multivariate analyses consisted of various logistic regression models and negative binomial regression models. Moreover, several split models were created in order to highlight potential differences between the online and traditional course settings and between criminal justice and non-criminal justice majors. Overall, each of the statistical models yielded interesting findings that have significant implications for collegiate academic misconduct policy.

Descriptive Statistics

As previously discussed, one intention for the descriptive statistics was to assess representativeness within the sample. In general, the goal for this study was to generate a sample that directly mirrored the student body at the selected institution. In having a more representative sample, more generalizable findings could be derived. With regards to academic school

diversity, the sample was quite representative of the campus community. In this study, each school was represented with a sufficient number of participants. Moreover, the number of participants within each school directly mirrored the campus enrollment within each of these colleges. As such, this sample was quite representative within the context of academic major. However, other statistics related to the sample's representativeness are also worth noting.

In this sample, participation from four groups exceeded the expected frequencies: female students, international students, graduate students, and "A" grade students. First, female students were more represented within this research. While the campus community had a female population of 54.2%, female students comprised of 66.4% of the participants within this study. Similarly, international students had higher response rate within the sample. While 9.4% of the campus community were international students, 19.1% of the participants claimed international citizenship within this research. For graduate students, the disparities were smaller yet still noteworthy. While 26.7% of the campus community are graduate students, this sample earned a 33.8% participation rate among graduate students. Lastly, high achieving students represented a large proportion of this sample. While this study had participants within all five GPA groups, 64% of the participants reported grade point averages in the "A" range. While the sample is not perfectly proportional to institutional demographics, this study still collected responses across a diverse group of students.

Demographic Variables

For this study, demographic information was collected from participants during the data collection process. Specifically, students were asked to report on eight demographic characteristics: age, graduate status, school, gender, grade point average, citizenship, academic major, and course type. As demonstrated in Table 6, the sample was primarily comprised of traditionally aged college students between the ages of 18 and 22. More precisely, 65.9% of the

sample fell into this age group of 18 to 22. In general, this was expected, as most college students fall within this age range. Alternatively, participants 23 years old or older comprised 34.1% of the sample.

Table 6

Demographic Variables Frequencies

Variable	N	%
Age (n = 1,084)		
18 years old	129	11.9
19 years old	203	18.7
20 years old	184	17.0
21 years old	113	10.4
22 years old	86	7.9
23 years old	76	7.0
24 years old	58	5.4
25 years old	47	4.3
26 years old	36	3.3
27 years old	30	2.8
28 years and older	122	11.3
Graduate (n = 1,084)		
undergraduate	718	66.2
graduate	366	33.8
School (n = 1,084)		
criminal justice & forensic sciences	399	36.8
arts & sciences	238	22.0
business	123	11.3
engineering	202	18.6
health sciences	122	11.3

Variable	N	%
Female (n = 1,084)		
non-female	364	33.6
female	720	66.4
GPA (n = 1,084)		
less than 2.0	6	0.6
2.00 – 2.49	23	2.1
2.50 – 2.99	82	7.6
3.00 - 3.49	279	25.7
3.50 - 4.00	694	64.0
Citizenship (n = 1,084)		
domestic student	877	80.9
international student	207	19.1
Academic Major (n = 1,084)		
non-criminal justice major	903	83.3
criminal justice major	181	16.7
Course Type (n = 1,084)		
traditional	553	51.0
online	531	49.0

In terms of graduate status, students were asked whether they were currently enrolled as an undergraduate student or graduate student. As demonstrated in Table 6, 66.2% of sample participants identified as undergraduate students, while 33.8% of the sample identified as graduate students. In general, this was an expected result, as the sampled institution has a larger undergraduate student population. However, this 2:1 ratio of undergraduates to graduate students suggests a slight overrepresentation by graduate students in this study.

In general, the participant frequencies across the different schools appear to mirror the institutional demographics for the sample university. At the sample university, the school of criminal justice and forensic sciences enrolls the largest proportion of students. As evidenced in Table 6, 36.8% of the participants belong to this academic school. The remaining participants were spread across the remaining four schools. In terms of academic diversity, this distribution of students is highly representative of the actual student body at the university.

For gender, students were offered three choices for identification purposes: male, female, and non-binary choice. Of the 1,084 participants in this study, 15 of them identified as non-binary choice. Since this study had so few non-binary participants, this would have posed a challenge within quantitative analysis. To remedy this issue, this gender variable was collapsed into a binary measure where students were separated into a non-female group and a female group. As shown in Table 6, 33.6% of the participants identified as a gender other than female, and 66.4% identified as female.

For grade point average, students were asked to report their current GPA range at the university. For this variable, students were offered five options: less than 2.0, 2.0 to 2.49, 2.5 to 2.99, 3.0 to 3.49, and 3.50 to 4.0. Table 6 highlights the frequency distributions across each of these GPA groups. Overall, 64.0% of the participants reported GPA's of 3.50 or greater, while 25.7% reported GPA's from 3.00 to 3.49. As such, only 10.3% of the participants had overall GPA's below the "B" range. Unfortunately, these frequencies would imply an overrepresentation of academically successful students within this study. To fully understand the impact of GPA on academic dishonesty, a greater diversity in the GPA groups would have been desired.

In terms of citizenship, students were asked to disclose their residential classification at the university. Specifically, participants would indicate whether they were a domestic student or an international student at the university. As shown in Table 6, 80.9% of the participants reported

domestic status at the university while 19.1% of the participants reported international status. In general, the sampled institution proved especially adequate in analyzing the effect of citizenship on academic dishonesty. The institution has an adequate enrollment of international students, as evidenced by the frequency participation within Table 6.

For this study, academic major was a central variable of interest. More precisely, cheating engagement among criminal justice majors was a primary inquiry for quantitative analysis. As shown in Table 6, this study garnered 16.7% participation by criminal justice majors. In general, this participation by criminal justice students both mirrors the campus percentage of criminal justice majors and provides an adequate group size for statistical analysis. Overall, this high percentage of criminal justice majors made it easier to identify notable differences within cheating intentions.

Lastly, participants were randomly separated into one of two groups based on course type. For students designated to the traditional group, their questions gauged their experiences with traditional classes. Alternatively, students assigned to the online survey group were asked similar questions concerning their remote learning experiences. Using an URL randomizer, student participants were randomly directed to one of these surveys. Furthermore, this randomizer produced a relatively equal distribution within each group. As shown in Table 6, 51% of the participants belonged to the traditional group, and 49% of the participants belonged to the online group. With a near even distribution between groups, statistical differences based on course type were examined in later analyses.

Peer Influences

For this analysis, students were asked about previous observations of peer cheating. More specifically, students were asked to report whether or not they had observed a peer engage in test cheating, plagiarism, or homework cheating. When looking at the overall data for all student

participants, certain findings can be interpreted. As shown in Table 7, among all students in the sample, personally witnessing homework cheating by a classmate had the highest prevalence at 28.7%. Moreover, 21.5% of the sample reported previous observations of peer test cheating, while 9.2% reported similar observations for plagiarism. In general, these findings would appear logical given the nature of these assessments. For example, homework assignments are typically assigned more frequently than papers or tests. As such, it would be reasonable for these students to observe peer homework cheating the most. In addition to these overall statistics, certain differences can be derived among the traditional student group and the online student group.

Table 7

Binary Independent Variables and Course Type

	Traditional		**Online**		**Overall**	
Variable	**N**	**%**	**N**	**%**	**N**	**%**
witnessed peer test cheating**						
no	452	81.7	399	75.1	851	78.5
yes	101	18.3	132	24.9	233	21.5
witnessed peer plagiarism						
no	502	90.8	482	90.8	984	90.8
yes	51	9.2	49	9.2	100	9.2
witnessed homework cheating***						
no	368	66.5	405	76.3	773	71.3
yes	185	33.5	126	23.7	311	28.7

Chi-Square Comparisons: *$p \leq .05$, **$p \leq .01$, ***$p \leq .001$

First, observations of peer test cheating appear different between the traditional group and the online group. Among traditional students, 18.3% had reported previous observations of test cheating among their peers. In contrast, the online students reported a 24.9% observation rate. In performing a chi-square analysis, these differences based on course type were significant at the .01 level. Based on these data, two inferences could be derived. First, the difference in percentages may imply that online students more readily observe their classmates engage in test copying. This is an interesting finding, as many online students are typically disengaged from their fellow classmates. These results may reflect the changing dynamics of online students in response to the Covid-19 pandemic. During the pandemic, online students may have interacted with more of their online peers than in previous semesters. Alternatively, it is also possible that online students may engage in higher rates of test cheating than traditional students. This result would be consistent with the hypotheses first outlined within this study. In general, online students have lesser instructor oversight within remote courses. As such, it would be logical for online students to engage in higher rates of test cheating than traditional students.

Second, previous observations of peer plagiarism also were measured within this study. Unlike the peer test cheating variable, the peer plagiarism variable yielded no disparities between the traditional students and online students. In both groups of students, identical results were produced, with 9.2% of participants reporting previous observations of plagiarism among peers. In general, this finding is reasonable, given that papers are typically completed outside of the classroom. As such, it would stand to reason that the process of writing class papers would be similar between traditional students and online students. The lower percentage of peer plagiarism observations is also worth noting. When compared against the other forms of cheating observations, peer plagiarism had the lowest rate of incidence. In general, these frequency

statistics may suggest that fewer students engage in plagiarism in both traditional and online courses.

Lastly, the data for peer homework cheating yielded interesting differences between the traditional students and the online students. As previously stated, homework cheating among peers had the highest reported frequency among all participants in the sample. However, when splitting up the sample based on course type, certain disparities were observed. Specifically, while homework cheating was the most observed form of academic dishonesty among the traditional students, this did not prove true for the online students. As evidenced in Table 7, 33.5% of traditional students had witnessed their peers cheat on a homework assignment, making it more widely observed than peer test cheating and peer plagiarism. Alternatively, only 23.7% of online students had personally witnessed a peer cheat on a homework assignment, earning a lower frequency than peer test cheating. In performing a chi-square analysis, these differences between traditional students and online students achieved statistical significance at the .001 level. This higher prevalence of observed peer homework cheating in traditional classes may reflect the inherent differences between traditional students and online students.

In general, traditional students may interact with their classmates more regularly. This would explain the differences in peer homework cheating statistics among traditional students and online students. Moreover, the 23.7% reporting of peer homework cheating among online students is also worthy of further discussion. Although this statistic is lower than the traditional student group, it is still objectively high considering online students may have limited interaction with their fellow peers. Again, such findings may reflect notable changes to online learning during the Covid-19 pandemic. During this pandemic, online students may have interacted with their peers more regularly than in previous online courses. This would explain the heightened rate of observations for peer homework cheating.

Likelihood of Detection

In addition to the binary independent variables, several independent variables were measured continuously. Among these measures were variables concerning the likelihood of cheating detection. For the likelihood of detection variables, students were asked to report their perceived likelihood of detection for test cheating, plagiarism, and homework cheating. In the survey, students were provided a scale of 0 to 10, where 0 represented a 0% likelihood of detection and 10 represented a 100% likelihood of detection. As a continuous measure, Table 8 highlights the minimum score, maximum score, mean average, and standard deviation for all of the detection variables. In addition to the overall sample statistics, averages for traditional students and online students were also computed. In doing so, differences between course types can be assessed.

Among the sample of students, participants rated the likelihood of test cheating detection as 5.22 (52.2% likelihood). In general, this detection variable for test cheating seems to have produced the most noticeable discrepancy among traditional students and online students. While online students reported lower likelihoods for test cheating detection, with a mean score of 4.6 (46.0% likelihood), traditional students reported higher likelihoods for test cheating detection, with a mean score of 5.82 (58.2% likelihood). In conducting an independent samples t-test on course type and likelihood of test cheating detection, the differences between groups were significant at the .001 level. In general, this finding is understandable as instructors cannot easily provide test oversight to online students. As such, the perceived likelihood for test cheating detection should be lower among the online cohort of participants.

When analyzing plagiarism and homework cheating, the respective means were 6.57 (65.7% likelihood) and 4.80 (48% likelihood) for the entire sample of students. When comparing

the reported means based on course type, the differences appear minimal. Although online students appear to have a slightly higher mean for plagiarism and a slightly lower mean for homework cheating, they do not appear noticeably different. More precisely, these minor differences could be attributed to standard error that is often present within sample statistics. In analyzing all three detection variables, initial assumptions can be derived. On average, college students seem to believe that engagement in plagiarism is the most detectable form of academic dishonesty. Alternatively, students seem to perceive homework cheating as the least detectable form of academic dishonesty.

Table 8

Continuous Independent Variables and Course Type

	Traditional					Online					Overall				
Variable	N	Min	Max	Mean	S.D.	N	Min	Max	Mean	S.D.	N	Min	Max	Mean	S.D.
likelihood of detection															
test cheating***	553	0	10	5.82	2.90	531	0	10	4.60	2.90	1,084	0	10	5.22	2.96
plagiarism	553	0	10	6.51	2.98	531	0	10	6.63	2.93	1,084	0	10	6.57	2.96
homework cheating	553	0	10	4.85	3.02	531	0	10	4.73	2.97	1,084	0	10	4.80	2.99
likelihood of reporting															
test cheating***	553	0	10	6.01	3.17	531	0	10	5.03	3.23	1,084	0	10	5.53	3.23
plagiarism	553	0	10	6.39	3.18	531	0	10	6.04	3.11	1,084	0	10	6.22	3.15
homework cheating	553	0	10	4.93	3.12	531	0	10	4.58	3.12	1,084	0	10	4.76	3.12
costs & benefits															
academic***	553	0	10	1.58	2.31	531	0	10	2.63	2.99	1,084	0	10	2.09	2.71
peers***	553	0	10	2.30	2.70	531	0	10	3.10	3.03	1,084	0	10	2.69	2.89
family***	553	0	10	1.71	2.27	531	0	10	2.50	2.76	1,084	0	10	2.10	2.55
quality of instruction***	553	0	10	6.59	2.51	531	0	10	5.19	2.75	1,084	0	10	5.91	2.81
software use															
webcams	---	---	---	---	---	531	0	10	4.62	3.67	---	---	---	---	---
Respondus	---	---	---	---	---	531	0	10	4.46	3.53	---	---	---	---	---
Turnitin	---	---	---	---	---	531	0	10	5.81	3.57	---	---	---	---	---

Independent Samples T-Tests: *$p \leq .05$, **$p \leq .01$, ***$p \leq .001$

Likelihood of Formal Reporting

For the likelihood of formal reporting variables, students were asked to disclose their perceived likelihood of being formal processed for test cheating, plagiarism, and homework violations. In the survey, students reported these perceived likelihoods using an 11-point scale, where 0 represented a 0% likelihood for formal reporting and 10 represented a 100% likelihood for formal reporting. When looking at the overall statistics, the average perceived likelihood for test cheating reporting was 5.53 (55.3% likelihood). In addition, the average perceived likelihood for plagiarism reporting was 6.22 (62.2% likelihood). Lastly, the average perceived likelihood for homework reporting was 4.76 (47.6% likelihood). Among the three offense types, plagiarism produced the highest mean. In general, this may imply that plagiarism is considered a more serious offense of academic dishonesty among students. Specifically, students may fear that plagiarism offenses will lead to more serious responses by an instructor.

When comparing statistics based on course type, certain differences are apparent. More precisely, the online students had slightly lower averages than the traditional students. For example, the means among traditional students for the likelihoods of test cheating reporting, plagiarism reporting, and homework cheating reporting were 6.01 (60.1% likelihood), 6.39 (63.9% likelihood), and 4.93 (49.3% likelihood) respectively. By comparison, online students scored a 5.03 (50.3% likelihood) for test cheating reporting, 6.04 (60.4% likelihood) for plagiarism reporting, and a 4.58 (45.8% likelihood) for homework reporting. While these raw averages appear different between traditional students and online students, test cheating reporting was the only variable to achieve a statistically significant difference. The differences in plagiarism reporting and homework reporting were not significantly different among traditional students and online students. Overall, though,

these statistics suggest that online students may perceive formal referrals to the Dean of Students as less likely.

Costs & Benefits

In the survey, participants were asked a series of questions concerning perceptions of costs towards academic misconduct. Specifically, students were asked to report how beneficial or how costly cheating was to their academic success, peer relationships, and familial relationships. During data collection, students were presented with a 0 to 10 scale, where scores closer to 0 represented cheating as a more costly behavior and scores closer to 10 represented cheating as more beneficial. As illustrated in Table 8, academic success had an average score of 2.09, peer relationships had an average score of 2.69, and familial relationships had an average score of 2.10. In general, these three averages did not deviate much from one another. On average, these statistics would suggest that students consider academic dishonesty to be more costly (than beneficial) to their academic, peer, and familial situations. In hindsight, the phrasing for the costs & benefits survey question could have been improved. More precisely, having both perceived costs and perceived benefits as opposite ends on one scale was not ideal. This question could have been improved by focusing on perceived costs and having students measure the costliness of cheating on a 0 to 10 scale.

When comparing these perceived costs and benefits between traditional students and online students, the mean averages appear to be different. In general, the traditional students reported lower mean averages across all three categories of the costs & benefits variables. More precisely, the traditional students had average scores of 1.58 for academic success, 2.30 for peer relationships, and 1.71 for familial relationships. In contrast, the online students had average scores of 2.63 for academic success, 3.10 for peer relationships, and 2.50 for familial relationships. In conducting an independent samples t-test for each of these perceived costs & benefits variables, statistically

significant differences were observed for all three. As such, these differences imply that traditional students consider academic dishonesty to be costlier than online students. Furthermore, these averages indicate that both traditional students and online students consider academic dishonesty to be more detrimental to their success.

Quality of Instruction

In the survey, participants were asked to rate the quality of education received in different courses. In general, this is a very pertinent question, as the Covid-19 pandemic led to a heavy shift towards online education. As such, this measure may reflect how students rate their online learning experiences when compared against traditional instruction. To gather data, students were presented with a 0 to 10 scale, where 0 represented very poor quality and 10 represented excellent quality. Among the entire sample of students, the mean score for quality was 5.91. This statistic indicates a slightly favorable impression towards educational quality. However, noticeable differences exist when comparing the means by course type.

For traditional students, the reported mean was 6.59. As such, traditional students seem to have a generally favorable view towards the quality of instruction within traditional courses. However, the online students reported a lower mean of 5.19. This would suggest that online students have a more neutral attitude towards the quality of instruction they receive in their online classes. When conducting an independent samples t-test, the difference in quality perceptions between traditional students and online students was significant at the .001 level. Overall, this is an important finding and worthy of further investigation. During the pandemic, online courses represented a heavy proportion of students' class schedules. As such, poorer perceptions toward the quality of online courses may have impacted engagement with academic dishonesty.

Software Use

For students assigned to the online group, three questions concerning anti-cheating software were included. More precisely, these students were asked how frequently online instructors would use webcams, the Respondus Lockdown Browser, and Turnitin® during their course assessments. As previously mentioned, online instructors often have limited oversight when a student completes an assessment remotely. To remedy these concerns, anti-cheating programs have become more widely used by college instructors. The purpose of these three variables was to determine how frequently online instructors utilized such resources within their courses.

For webcams and Respondus, these variables produced mean averages of 4.62 and 4.46. These statistics would suggest that both webcams and Respondus are used somewhat infrequently for online exams. Alternatively, Turnitin® had a 5.81 mean average, which indicates that this program was used more frequently by instructors for plagiarism detection. Objectively, these mean averages are rather low, and higher mean averages might have been expected.

For the variables related to test cheating, students were asked if they would potentially engage in one of four behaviors: copying from a classmate during a test, providing answers to a fellow student during a test, receiving questions or answers ahead of a test, and utilizing notes during an exam. For homework cheating, students were asked if they would potentially collaborate on a homework assignment when it is not permitted by an instructor. Lastly, students were asked if they would engage in a form of plagiarism. More specifically, students were asked if they would submit a paper partially or completely done by someone else, plagiarize public material into a paper, add false citations to a paper in order to lengthen the reference list, and whether they would copy sentences without citing the source. Higher mean averages for these software programs would imply that online instructors are fully utilizing anti-cheating resources available to them for their

remote courses. Unfortunately, these statistics suggest the contrary, which could have an impact on overall cheating rates among online students.

Dependent Variables

As listed in Table 9, nine dependent variables were created to measure academic dishonesty among college students. Each of these dependent variables reflect a form of test cheating, homework cheating, or plagiarism. For the variables related to test cheating, students were asked if they would potentially engage in one of four behaviors: copying from a classmate during a test, providing answers to a fellow student during a test, receiving questions or answers ahead of a test, and utilizing notes during an exam. For homework cheating, students were asked if they would potentially collaborate on a homework assignment when it is not permitted by an instructor. Lastly, students were asked if they would engage in a form of plagiarism. More specifically, students were asked if they would submit a paper partially or completely done by someone else, plagiarize public material into a paper, add false citations to a paper in order to lengthen the reference list, and whether they would copy sentences without citing the source.

Table 9

Dependent Variables and Course Type

Variable	Traditional N	Traditional %	Online N	Online %	Overall N	Overall %
test cheating (copying)**						
no	405	73.2	346	65.2	751	69.3
yes	148	26.8	185	34.8	333	30.7
test cheating (collusion)**						
no	397	71.8	337	63.5	734	67.7
yes	156	28.2	194	36.5	350	32.3
test cheating (advance)						
no	325	58.8	328	61.8	653	60.2
yes	228	41.2	203	38.2	431	39.8
test cheating (cribnotes)***						
no	422	76.3	232	43.7	654	60.3
yes	131	23.7	299	56.3	430	39.7
homework (collusion)						
no	278	50.3	277	52.2	555	51.2
yes	275	49.7	254	47.8	529	48.8
plagiarism (collusion)						
no	471	85.2	441	83.1	912	84.1
yes	82	14.8	90	16.9	172	15.9
plagiarism (public material)						
no	455	82.3	419	78.9	874	80.6
yes	98	17.7	112	21.1	210	19.4
plagiarism (padding)						
no	365	66.0	340	64.0	705	65.0
yes	188	34.0	191	36.0	379	35.0
plagiarism (copying)						
no	364	65.8	362	68.2	726	67.0
yes	189	34.2	169	31.8	358	33.0

Chi-Square Comparisons: *$p \leq .05$, **$p \leq .01$, ***$p \leq .001$

Test Cheating (Copying)

The first dependent variable relates to test cheating. Specifically, participants were asked if they would copy from a classmate during a test. In terms of overall statistics, roughly 31% of participants admitted to the possibility of engaging in test copying in a future class. Alternatively, 69% reported no possibility of engaging in this form of academic dishonesty. When comparing the traditional students to the online students, test copying appeared slightly more likely among the online students. Comparatively, 34.8% of online students admitted to the possibility of test copying, which is 8.0 percentage points higher than the traditional group. In conducting a chi-square analysis, these differences between traditional students and online students were significant at the .01 level. In general, this finding aligns with the early hypotheses of this study. Generally speaking, online students have less instructor oversight than traditional students. As such, test copying should be more prevalent within online courses.

Test Cheat (Collusion)

The second dependent variable, test collusion, also yielded similar results among the traditional students and the online students. For test collusion, students were asked whether they would supply answers to another student during an exam in a future class. Overall, the statistics for test collusion were quite similar to the test copying variable. Among all the participants, roughly 32% recognized the possibility of engaging in test collusion, whereas 68% reported no likelihood of engagement. Similar to test copying, more online students reported the possibility of test collusion. Specifically, online students had an 8.3 higher percentage than traditional students. Furthermore, results from chi-square testing reveal that this difference between traditional students and online students was significant at the .01 level. As previously stated, this finding is consistent with arguments concerning heightened academic dishonesty within online courses.

Test Cheat (Advance)

The third dependent variable relates to test cheating and whether a student would receive advanced test questions or answers from a peer. Based on the data presented in Table 9, this dependent variable revealed higher engagement than the previous test cheating variables. For this variable, nearly 40% of students admitted to the possibility for this form of test cheating. In general, this finding was also consistent between for course types. When comparing traditional students against the online students, the rates were quite similar. Specifically, there was only a 3.0 percentage point difference between the two groups. Interestingly, this dependent variable behaved differently than expected. For receiving test questions and answers in advance, this form of academic dishonesty was less prevalent among the online students. Overall, this finding may relate to the nature of online courses. For an instructor teaching multiple online sections, an exam may be scheduled at the same time for all students. Alternatively, an instructor teaching multiple traditional sections may administer an exam during different class times, making this form of academic dishonesty more likely.

Test Cheat (Cribnotes)

In this study, the fourth dependent variable proved to have the greatest group disparities among the test cheating behaviors. For this variable, students were asked whether they would utilize notes during an exam when a professor does not allow such references. In terms of overall frequencies, roughly 40% of the sample admitted that engagement in this form of cheating was a possibility for them. However, the disparities are quite large when students are separated based on course type. Among the traditional group, 23.7% of the students reported a possible likelihood of utilizing cribnotes during an exam. In contrast, the online group had 56.3% of students reporting the potential for this academic dishonesty. Moreover, this behavior had the highest likelihood of the

nine cheating variables among the online group of students. When conducting a chi-square test on course type and cribnotes use, the difference between groups was significant at the .001 level. This finding strongly supports the argument that instructor oversight during exams may have a large impact on student cheating behaviors. Since online students typically have more autonomy during tests, they may be more inclined to reference notes, despite instructor objections.

Homework Cheating

For the fifth dependent variable, students were asked about homework cheating and their likelihood of collaborating with other students on assignments when it is not permitted by an instructor. In terms of overall statistics, roughly 49% of the sample reported a willingness to engage in homework cheating within their respective courses. When examining the differences between traditional students and online students, the frequency rates were quite similar, with roughly 50% of the traditional students recognizing the possibility against roughly 48% of the online students. Furthermore, among the traditional students, homework collusion appeared to have the highest likelihood of the nine cheating variables. Despite having a slightly lower likelihood, homework collusion was still quite high among the online students. For online students, regular interactions with peers is often absent within remote courses. As such, collaborating with online peers should prove more difficult among these students. However, based on the statistics produced within this data, homework cheating behaviors actually appear similar among traditional students and online students.

Plagiarism (Collusion)

The sixth dependent variable within this study was a measure of plagiarism. Specifically, students were asked if they would submit a paper done partly or entirely by someone else within their respective courses. Among the entire sample of students, only 15.9% disclosed possible

engagement within this form of plagiarism. When splitting up the students based on course type, the findings were fairly similar with 14.8% of traditional students reporting a possibility, versus 16.9% among the online students. In general, paper collusion had the lowest likelihood across all students within the sample. This could imply that submitting unoriginal papers is considered a more severe offense among college students. Additionally, with widespread use of anti-plagiarism software, students may feel less comfortable engaging in this type of cheating.

Plagiarism (Material)

In regards to plagiarizing public material, the statistics shared some similarities with the paper collusion variable. For this seventh dependent variable, students were asked whether they would plagiarize public material in a course paper. Like paper collusion, the prevalence of this variable was comparatively low in the context of all nine dependent measures. Overall, 19.4% of the sample admitted to possibly plagiarizing public material, yielding the second lowest figure among all academic dishonesty variables. Moreover, the traditional students and the online students reported similar rates of roughly 18% and 21%, respectively. Much like paper collusion, students may perceive this form of plagiarism as costlier given the use of anti-plagiarism software by instructors.

Plagiarism (Padding)

In this study, the eighth dependent variable measured bibliography padding behaviors among college students. For this variable, students were asked whether they would add false citations to a bibliography in order to lengthen a course paper. For this form of plagiarism, 35% of the sample acknowledged citation padding as a possibility within a future course. When comparing responses based on course type, the traditional students and the online students reported similar likelihoods. For traditional students, 34% of this group reported a possibility of paper padding. In

contrast, 36% of online students reported the potential for paper padding within their courses. When compared against the previous two plagiarism dependent variables, paper padding appears to have a notable increase in potential engagement among survey participants. This may suggest that students perceive this form of plagiarism as less risky or serious.

Plagiarism (Copying)

Lastly, students were asked whether they would copy a few sentences of material into a course paper without citing the source. In general, the findings for this plagiarism variable were quite similar to those of paper padding. Among the entire sample of students, 33% reported a chance for this type of plagiarism within a future course. Furthermore, roughly 34% of traditional students acknowledged the possibility of copying material. Similarly, roughly 32% of the online students admitted to the same possibility of copying material.

Bivariate Statistics for Independent and Dependent Variables

Chi-Square Statistics

In bivariate analyses, chi-square statistics are useful when a dependent variable is measured on a binary scale. For this study, the nine dependent variables were coded dichotomously, making chi-square models the appropriate test for this stage of analysis. In general, chi-square statistics analyze frequencies across groups. When a chi-square statistic yields a statistically significant p-value, this suggests that the analyzed groups are not equally proportioned in frequencies. Rather, such a finding would imply that one of the groups has a frequency that differs from the expected value assumed for equal proportions. As shown in Table 10, the relationships between the individual independent and dependent variables were examined.

Table 10

Chi Square Statistics

	Test Copying	Test Collusion	Test Advance	Test Cribnotes	Homework Collusion	Plagiarism Collusion	Plagiarism Material	Plagiarism Padding	Plagiarism Copying
Graduate	14.59***	9.28**	21.73***	12.74***	39.01***	5.16*	9.63**	3.54	.700
School	13.99**	10.64*	21.29***	16.51**	33.75***	12.59**	16.13**	7.59	10.42*
Female	.154	.793	2.38	.199	.356	24.71***	13.39***	2.10	6.60**
GPA	13.72**	5.04	4.00	7.63	6.03	27.31***	15.16**	13.89**	10.72*
Citizenship	1.62	.402	4.41*	8.19**	27.66***	26.10***	31.93***	.299	4.31*
Major	.603	.006	.115	.489	.579	.367	2.12	.215	.045
Course Type	8.30**	8.59**	1.02	120.4***	.389	.913	1.97	.464	.677
Peer Exams	28.70***	39.55***	39.04***	30.56***	64.50***	.159	.287	5.80*	2.02
Peer Homework	15.98***	23.26***	66.30***	15.48***	122.03***	.378	1.13	29.04***	5.41*
Peer Plagiarism	6.59**	6.91**	8.06**	1.85	10.19***	10.23***	6.54*	4.88*	3.17

*$p \leq .05$ **$p \leq .01$ ***$p \leq .001$

Test Cheating (Copying)

In conducting individual chi-square statistics, several independent variables proved statistically significant on a student's likelihood to test copy. First, four variables were statistically significant at the .01 level: school, grade point average, course type, and previous observations of peer plagiarism. For school and grade point average, the data suggest that the likelihood for test copying is lower among certain academic schools and among students with certain grade point averages. More specifically, the data indicate that health science, engineering students, and students with "A" averages are less likely to engage in test copying. Furthermore, the results for course type and peer observations also suggest that test copying is more likely among online students and students who have personally witnessed peer plagiarism.

Additionally, three independent variables proved even more statistically significant with the likelihood of test copying, achieving a p-value of .001 or less: graduate status, previously observing peer test cheating, and previously observing peer homework cheating. For graduate status, significant differences exist between undergraduates and graduate students. More precisely, undergraduate students seem to have a higher chance of test copying than graduate students. For prior cheating observations, students who have previously witnessed a peer cheat on a test and on a homework assignment displayed a greater willingness to engage in test copying. This latter finding was especially interesting. Based on these chi-square statistics, it appears that witnessing any form of cheating has an influence on this specific form of test cheating.

Test Cheating (Collusion)

In analyzing test collusion, the chi square models yielded several statistically significant findings. First, school achieved a p-value less than .05. This suggests that significant differences exist between students of varying academic schools. More precisely, engineering students and

business students appeared slightly less likely to engage in test cheating collusion. Moreover, health science students appear the least likely to engage in test collusion among the sample of students. In addition, three independent variables proved significant at the .01 level: graduate status, course type, and previously observing peer plagiarism. These chi-square values imply that undergraduate students, online students, and students who have previously observed peer plagiarism are more likely to engage in test cheating collusion. Lastly, the remaining two peer variables achieved statistical significance at the .001 level. With these p-values, previous observations of peer test cheating and peer homework cheating seem to have a strong influence on whether a participant would give answers to another student during an exam.

Test Cheating (Advance)

For the variable of test cheating advance, students were asked whether they would receive questions or answers prior to an examination. In performing several chi-square analyses, multiple independent variables proved influential on a student's likelihood of engaging in this form of test cheating. At the .05 level, significant differences are observed between domestic students and international students, with domestic students displaying higher than expected frequencies. At the .01 level, significant differences in cheating occurred between students who had previously observed peer plagiarism and those who had not witnessed peer plagiarism. Finally, four variables proved highly significant on test cheating advance, achieving p-values less than .001. These variables include graduate status, academic school, previously observing peer test cheating, and previously observing peer homework cheating. First, these results imply that undergraduate students were more likely to receive questions and answers before an exam. Second, students belonging to the schools of engineering, business, and health sciences reported lower likelihoods for this form of test cheating. Lastly, students who had previously observed peer test cheating and peer homework cheating had higher odds for this test cheating variable.

Test Cheating (Cribnotes)

In this study, students were asked if they would utilize notes during an examination when an instructor does not permit such actions. Through these chi-square statistics, several variables proved statistically relevant on a student's use of cribnotes. At the .01 level, academic school and student citizenship both yielded significant differences. Upon closer examination of the chi-square analyses, students in the engineering school and the health science school were less likely to use cribnotes on an exam. For citizenship, use of cribnotes appeared more prevalent among domestic students than international students.

Additionally, four of the independent variables proved highly influential on use of cribnotes, reaching significance at the .001 level. These variables include graduate status, course type, previous observations of peer test cheating, and previous observations of peer homework cheating. For graduate status, undergraduates expressed a greater willingness to use unauthorized notes during an examination, whereas graduate students appeared less likely to do the same. For course type, the results of this chi-square analysis seem to substantiate the observations within the descriptives section of this study. As previously mentioned, intentions to use cribnotes appeared far greater within the online cohort of students than among traditional students. Lastly, intentions to use cribnotes appeared greater among students who had previously observed their peers cheat on a homework assignment or exam.

Homework Cheating

For the homework collusion variable, students were asked whether they would work with other students on a homework assignment when an instructor does not permit peer collaboration. In running multiple chi-square analyses, six variables proved highly significant at the .001 level: graduate status, academic school, citizenship, previously observing peers cheat on an exam, previously observing peers plagiarize, and previously observing peer homework cheating. For

the graduate variable, graduate students had higher than expected intentions to homework cheat, whereas undergraduate students appeared to have lower than expected intentions. For the frequencies for homework cheating intentions across the various academic schools, actual counts among the different groups appeared to deviate considerably from the expected counts. This would imply that noticeable disparities exist among students of certain academic colleges. Specifically, criminal justice & forensic science students had much higher than expected counts, while health science students had counts much lower than expected. For citizenship, domestic students reported a greater likelihood of homework cheating when compared against international students. Finally, all three peer variables proved highly influential on a student's willingness to collaborate on homework assignments. This finding implies that any observation of academic dishonesty among peers can have a significant influence on homework cheating.

Plagiarism (Collusion)

For the plagiarism collusion variable, students were asked whether they would submit a paper done partially or completely by someone else. Based on the results of the chi-square analyses, several variables influenced this form of plagiarism. First, graduate ($p \leq .05$) and school ($p \leq .01$) proved significant in the chi-square models. Specifically, graduate students, business students, and engineering students reported higher than expected frequencies for plagiarism collusion intentions. In addition, four independent variables achieved significance at the .001 level: identifying as a female, grade point average, citizenship, and previously observing peer plagiarism. Examination of this variable implies that females are less likely to submit plagiarized papers than non-females. For grade point average, students reporting a 3.50 – 4.00 GPA disclosed lower intentions to engage in plagiarism collusion. In regards to citizenship, international students appear more likely to engage in this form of plagiarism. While international students appeared less likely to engage in different forms of test cheating, the

opposite appears true for this form of plagiarism. Lastly, previously observing a plagiarism among other peers seems to have an impact on student behavior. More precisely, witnessing these behaviors seems to promote similar behaviors among students.

Plagiarism (Material)

In this study, the plagiarism material variable reported a student's likelihood for plagiarizing public material in a course paper. Through bivariate analysis, four independent variables proved significant at the .01 or .05 levels with this form of plagiarism: graduate ($p \leq .01$), school ($p \leq .01$), grade point average ($p \leq .01$), and peer plagiarism ($p \leq .05$). Specifically, significant frequency disparities can be observed among the different groups within these four variables. First, graduate students reported higher than expected frequencies for intentions to plagiarize public material in a course paper. Second, students in the health sciences and the school of criminal justice & forensic sciences had lower than expected frequencies for this form of plagiarism. Third, students with a GPA higher than a 3.50 also reported lower than expected frequencies for intentions to plagiarize public material. Lastly, students who had previously observed peer plagiarism had a higher likelihood for engaging in plagiarism themselves.

Furthermore, female status and citizenship proved especially influential within these models, reaching statistical significance at the .001 level. Based on the chi-square findings, females are less likely to engage in this form of plagiarism than non-females. In terms of citizenship, the findings directly mirror those established for the plagiarism collusion variable. In general, international students appear more likely to plagiarize public material in a course paper than domestic students.

Plagiarism (Padding)

For plagiarism padding, several variables achieved statistical significance at varying p-levels. First, three of the independent variables proved moderately significant on a student's

likelihood of adding false citations to a bibliography. These variables include grade point average ($p \leq .01$), previously observing peer test cheating ($p \leq .05$), and previously observing peer plagiarism ($p \leq .05$). These findings indicate that this form of plagiarism was more likely among students with a GPA less than 3.50 and among students who had previously observed both peer test cheating and peer plagiarism. Interestingly, the most significant variable within across this dependent variable was previous observations of homework cheating, reaching significance at the .001 level. In contrast, previous observations of peer plagiarism did not have the most significant impact on a student's likelihood for padding a bibliography. Rather, this analysis indicates that personally witnessing peer homework cheating had the greatest influence on whether a student engages in this form of plagiarism.

Plagiarism (Copying)

In analyzing a student's likelihood of copying sentences into a paper without citing, the bivariate analyses yielded limited significant results for the independent variables. When compared against the other eight forms of cheating, this dependent variable was the only analysis that failed to produce a finding at the .001 significance level. At the .05 level, four variables proved influential on this form of plagiarism: school, grade point average, citizenship, and previously observing peer homework cheating. The chi-square statistics indicate that health science students and students with a 3.50 – 4.00 GPA had lower than expected counts for intentions to copy sentences without citing. Furthermore, this form of academic dishonesty appears more likely among international students and students who have previously observed peer cheating on homework assignments. Among the analyzed independent variables, the female variable appeared to have the strongest influence on this form of plagiarism, reaching significance at the .01 level. Based on this bivariate statistic, females appear less likely to copy sentences into papers without properly citing the source.

Cronbach's Alpha

When creating composite measures, internal consistency across the variables is critical. In order to assess the internal consistency, a Cronbach's Alpha score is often generated. In general, a Cronbach's Alpha coefficient of at least .70 is desired, as this would imply adequate internal consistency across the selected variables (Cortina, 1993). For the first composite measure, the four test cheating variables were combined into a singular measure of test cheating, measured on a scale from 0 to 4. This composite measure represents how many forms of test cheating a student would be willing to engage in within their respective courses. Overall, this composite score achieved a Cronbach's Alpha of .868, suggesting that the four test cheating variables are highly correlated and comprise an appropriate measure.

Similarly, the four plagiarism variables were also combined into a composite measure, expressed on a scale of 0 to 4. For the overall plagiarism variable, a Cronbach's Alpha of .824 was generated. This also suggests that this composite score for plagiarism is appropriate for data analysis. Lastly, all nine dependent variables were used to create an overall academic dishonesty variable, which was measured on a scale from 0 to 9. For this composite score, a Cronbach's Alpha value of .900 was generated. This demonstrates internal consistency across all nine variables, suggesting that this is an appropriate measure that represents cheating overall among the sample.

Concerning the independent variables, two composite measures were created for peer influences and perceived costs & benefits. For peer influences, the three dichotomous variables pertaining to peer observations of cheating were combined into a scale measure of 0 to 3. For this composite score, a Cronbach's Alpha coefficient of .670 was produced. As previously stated, Cronbach Alpha scores of .70 are desired when generating composite measures. When scores are above .70, concerns for internal consistency can be minimized. In this case, the peer influences

composite score fell slightly short of this desired benchmark. This composite measure was utilized in subsequent quantitative analyses, but the marginal internal consistency should be kept in mind when interpreting the results.

Finally, the three cost & benefits variables were combined into a single overall measure. For the cost & benefits variables, students were asked how costly cheating would be to their academic, peer, and familial success. These variables were measured on a scale of 0 to 10, where 0 represented more costly and 10 represented more beneficial. To create an overall perceived costs & benefits composite variable, responses for the three costs & benefits variables were averaged. In determining the internal consistency across these variables, a Cronbach's Alpha value of .889 was produced. This coefficient demonstrates that the three costs & benefits measures were highly correlated with one another. As such, the costs & benefits composite variable should prove appropriate within bivariate and multivariate analysis.

Analysis of Variance (ANOVA)

As previously demonstrated by the chi-square statistics, significant differences in academic dishonesty appeared across academic schools and students with different grade point averages. To further investigate the nature of these differences, this study utilized analysis of variance (ANOVA) during data analysis. Unlike chi-square models, ANOVA's require dependent variables that are measured on a scale. Accordingly, the three composite measures for cheating served as the dependent variables in these models. As presented in Table 11, through use of ANOVA modeling, several key findings were derived based on academic schools and grade point average (GPA).

Table 11

Analysis of Variance (ANOVA) F-Scores

	Test Cheating Overall	Plagiarism Overall	Cheating Overall
School	**5.28*** **	**3.09***	**4.46*** **
GPA	2.32	**5.73*** **	**4.21** **

*p ≤ .05 **p ≤ .01 ***p ≤ .001

Overall Test Cheating

When analyzing overall test cheating, academic school yielded a p-value less than .001 within ANOVA modeling. When an ANOVA produces a statistically significant p-value, it implies that at least one of the groups within the independent variable is different from the others. For academic school, this statistic suggests that at least one of the academic schools is different from the others in overall test cheating. In order to identify the nature of these differences, use of post-hoc comparisons are often pursued. To select the appropriate post-hoc analysis, a heterogeneity of variance test must first be calculated. Specifically, the Levene's statistic will determine whether equal variances are assumed (Kremelberg, 2011). For this analysis, the Levene probability was less than .05, indicating that equal variances were not assumed (Kremelberg, 2011). When equal variances are not assumed, only certain post-hoc tests are appropriate. Among these analyses, Tamhane's is one test that does not assume equal variances (Kremelberg, 2011). In this ANOVA model, Tamhane's post-hoc comparisons reveal that test cheating intentions among health science students are significantly different from the criminal justice & forensic science students ($p \leq .001$). In addition, significant differences also exist between health science students and students of arts & sciences ($p \leq .001$). For these comparisons, students in the health sciences demonstrated lower likelihoods for test cheating.

Overall Plagiarism

For overall plagiarism intentions, both academic school and grade point average proved statistically significant within the ANOVA models. In regards to academic school, this variable was significant at the .05 level, indicating that at least one school was significantly different in the number plagiarism intentions. Levene's statistic was then calculated in order to assess equal variances. With a p-value less than .05, this indicated that equal variances are not assumed in this model. As such, Tamhane's post-hoc comparisons were appropriate in identifying the differences between groups. Through use of Tamhane's post-hoc comparisons, it was determined that students in the health sciences were different from students in criminal justice & forensic sciences ($p \leq .05$), arts & sciences ($p \leq .05$), business ($p \leq .05$), and engineering ($p \leq .01$). In general, health science students displayed the lowest potential to plagiarize on assignments among the entire sample of students.

In terms of grade point average, interesting findings were also derived from the ANOVA model. Through ANOVA testing, grade point average achieved a p-value of less than .001. This implies that at least one GPA group was significantly different in plagiarism intentions. It might be expected that the greatest disparity in plagiarism intentions would be between the lowest tier and highest tier of GPA groups. However, the most significant differences exist between "B" range students and "A" students. This finding is derived from Tamhane's post-hoc analyses where differences between the 3.00 – 3.49 group and the 3.50 – 4.00 group were significant at the .01 level.

Academic Dishonesty Overall

When looking at overall academic dishonesty intentions among students, academic school and grade point average both proved statistically significant in their respective ANOVA models. In terms of academic school, the ANOVA for overall cheating intentions yielded similar

results as the ANOVA for test cheating. Specifically, academic school proved significant at the .001 level, and further Tamhane's post-hoc analyses provided context into these differences between schools. As previously stated, Tamhane's post-hoc analyses are most appropriate when equal variances are not assumed. Per the results of the Levene's test, equal variances were not assumed in this model. Similar to the post-hoc analyses for test cheating, the most significant differences in overall cheating intentions occurred between health science students and those in the criminal justice & forensic sciences school ($p \leq .001$) and the arts & sciences school ($p \leq .001$). More precisely, health science students displayed lower likelihoods for engaging in dishonest academic behaviors. In general, this was an unexpected finding, as this research study had initially hypothesized that criminal justice majors would display the fewest cheating intentions among a body of students.

For grade point average and overall cheating intentions, the ANOVA model proved statistically significant at the .01 level, suggesting that at least one group is different. Use of Tamhane's post-hoc analyses revealed that the greatest differences in overall cheating intentions occurred between students with a 3.00 – 3.49 GPA and students with a 3.50 – 4.00 GPA. Specifically, students in the "B" range for GPA appear more likely to engage in some form of cheating. These results mirror those found in the overall plagiarism analysis. Overall, these findings have noteworthy policy implications for college instructors. This suggests that moderately successful students are at the greatest risk for academic dishonesty, and that anti-cheating efforts should consider this group of students. However, the results of this ANOVA model may be the result of underrepresentation by lower performing students within the sample. As discussed in the descriptives section, roughly 90% of the sample belonged to the 3.00 – 3.49 GPA group and the 3.50 – 4.00 GPA group. As such, fewer participants within the lower GPA groups could have skewed the results of this analysis.

Pearson Correlation Coefficients (Continuous Variables)

Pearson correlation coefficients are useful for bivariate analyses that involve independent and dependent variables measured on a continuous scale. In general, these coefficients measure how closely correlated the two variables are to one another, and the direction of their association (see Table 12). Specifically, a positive coefficient would suggest that as one variable increases, the other variable also increases. Alternatively, a negative coefficient would imply that as one variable increases, the other variable decreases.

Table 12

Pearson Correlation Coefficients for Continuous Variables

	Test Cheating Overall	Plagiarism Overall	Academic Dishonesty Overall
Age	**-.159*** **	-.040	**-.128*** **
Quality Perceptions	**-.208*** **	**-.092** **	**-.172*** **
Webcam Use	**-.141*** **	.063	-.065
Respondus Use	-.063	.067	-.008
Turnitin Use	**-.145*** **	-.063	**-.119** **

*p ≤ .05 **p ≤ .01 ***p ≤ .001

Overall Test Cheating

For student age, this variable appears to have a significant negative relationship with test cheating. More precisely, as student age increases, the likelihood for test cheating appears to decrease. This finding is consistent with prior research concerning academic dishonesty and the initial age hypothesis within this study (Lambert & Hogan, 2004; McCabe & Trevino, 1999; McCabe et al., 2012). For the quality perceptions variable, students were asked to report their

level of satisfaction with the education they have received in their respective course types. Based on the correlation coefficient for this variable, the likelihood for test cheating appears to decrease as overall satisfaction increases among students. In general, this finding seems logical, as satisfied students should behave more positively within their respective courses.

Lastly, students in the online course group were asked about the frequency of anti-cheating software within remote classes. Using this data, the correlation coefficients determined how the software may impact the likelihood for test cheating among online students. Among the three types of anti-cheating software, prior use of webcams and Turnitin® appeared impact the likelihood of test cheating. More precisely, greater previous use of webcams and Turnitin® was associated with lower potential for test cheating.

Overall Plagiarism

When looking at overall plagiarism behaviors, perceptions of quality proved statistically significant at the .01 level. With a negative correlation coefficient, this statistic suggests that the overall risk for plagiarism decreases as student perceptions of quality increase. However, it is worth nothing that the coefficient value for overall plagiarism is lower than the coefficient for overall test cheating. With a weaker correlation coefficient and p-value, perceptions of course quality appear to have a lesser effect on future plagiarism behaviors than on future test cheating.

Overall Academic Dishonesty

In examining the overall likelihoods for academic dishonesty, three of the correlation coefficients achieved statistical significance: student age, quality perceptions, and use of Turnitin®. In general, the findings for these variables are consistent with the previous findings. Specifically, student age had a negative relationship with overall cheating likelihood, achieving significance at the .001 level. The coefficient value implies that as student age increases, the likelihood for academic dishonesty decreases. Perceptions of course quality also achieved

statistical significance at the .001 level. The coefficient indicates that as perceptions of quality increase among students, their likelihood for academic dishonesty decreases. Finally, use of Turnitin® proved significant at the .01 level. This coefficient implies that the odds for cheating decreases as prior use of Turnitin® increases.

Pearson Correlation Coefficients (Rational Choice Variables)

Test Cheating Overall

When examining overall test cheating, all of the rational choice independent variables proved statistically significant at the .001 level. First, the formal reporting variables produced interesting findings. Specifically, the correlation coefficients show that all three formal reporting variables proved significant with overall test cheating. While it was expected that formal reporting for test cheating would impact the likelihood for test cheating, the reporting variables also were significantly associated with plagiarism and overall cheating. This may suggest that a student's experiences with one form of cheating may impact attitudes towards other cheating. As demonstrated in Table 13, the three reporting variables and the composite measure of reporting each have a negative relationship with test cheating. These statistics imply that the likelihood for test copying decreases as the overall likelihood for formal reporting increases. This finding directly supports one of the key hypotheses for this study. Using rational choice theory as a framework, this study posited that academic dishonesty would be more prevalent when the likelihood for formal reporting is low.

Table 13

Pearson Correlation Coefficients for Rational Choice Variables

	Test Cheating Overall	Plagiarism Overall	Academic Dishonesty Overall
Likelihood of Reporting (Test Cheating)	**- .186*** **	**-.061***	**-.141*** **
Likelihood of Reporting (Plagiarism)	**-.161*** **	**-.112*** **	**-.146*** **
Likelihood of Reporting (Homework)	**-.177*** **	-.038	**-.140*** **
Likelihood of Reporting (Overall)	**-.188*** **	**-.076** **	**-.153*** **
Likelihood of Detection (Test Cheating)	**-.167*** **	-.034	**-.114*** **
Likelihood of Detection (Plagiarism)	**-.109*** **	**-.089** **	**-.099*** **
Likelihood of Detection (Homework)	**-.170*** **	-.023	**-.126*** **
Likelihood of Detection (Overall)	**-.170*** **	-.056	**-.129*** **
Peer Influences (Overall)	**.216*** **	**.080** **	**.199*** **
Costs & Benefits (Academic Success)	**.546*** **	**.410*** **	**.543*** **
Costs & Benefits (Peer Relationships)	**.483*** **	**.330*** **	**.472*** **
Costs & Benefits (Familial Relationships)	**.521*** **	**.386*** **	**.516*** **
Costs & Benefits (Overall)	**.570*** **	**.413*** **	**.562*** **

*p ≤ .05 **p ≤ .01 ***p ≤ .001

Similarly, the three detection variables and the composite measure for instructor detection produced negative coefficients that proved statistically significant at the .001 level. Like formal reporting, this study initially hypothesized that academic dishonesty would increase when the likelihood for instructor detection was low. As demonstrated by the direction and significance of the coefficients, this hypothesis appears accurate among the study's sample. More specifically, the likelihood for test cheating decreased as instructor detection increased. Additionally, the significance levels for plagiarism detection and homework detection may imply that student engagement in test cheating is influenced by instructor vigilance on other assignments.

Additionally, the peer influences composite measure proved statistically significant with overall test cheating. The peer score reflects the number of cheating behaviors that a student had personally witnessed. More precisely, students were asked whether they had ever observed peer test cheating, plagiarism, or homework cheating. As such, this peer score was scaled from 0 to 3, with 3 representing previous observations for all forms of academic dishonesty. The correlation coefficient for the peer composite score suggests that overall test cheating odds were higher among students with more observations of peer cheating.

Among the rational choice variables within this study, the three costs & benefits questions embody the underlying framework of this theory. For rational choice theory, careful consideration of the perceived costs and benefits of a decision is a hallmark within this criminological framework. In application to this study, it was expected that academic dishonesty would be more prevalent when the perceived benefits of these actions outweigh the costs. As evidenced by the correlation coefficients in Table 13 for the costs & benefits variables, this appears to be the case among the sample of students. Specifically, academic dishonesty appears to increase when there are perceived benefits to academic success, peer relationships, and

familial relationships. In addition, the correlation coefficients for these variables were the strongest shown in Table 13.

Plagiarism Overall

When looking at overall intentions for plagiarism, the rational choice variables in this analysis seemed to have varied results compared to what was presented in the overall test cheating analyses. Unlike overall test cheating, where all of the correlation coefficients achieved statistical significance at the .001 level, only certain variables achieved significance with overall plagiarism. Among the reporting variables, the likelihood for plagiarism reported proved most significant with intentions to plagiarize, achieving a p-value of less than .001. In general, this relationship was expected, as formal reporting for plagiarism should discourage engagement in plagiarism. Additionally, reporting for test cheating and the overall composite measure for reporting achieved significance at the .05 and .01 levels. This suggests that perceptions of formal reporting for other forms of cheating also impact a student's likelihood for plagiarism.

In analyzing the correlation coefficients for the detection variables, only plagiarism detection proved significant at the .01 level. With a negative coefficient, this implies that the odds for plagiarism decreases as perceived instructor detection for plagiarism increases. Unlike the test cheating analyses, other forms of cheating detection do not impact a student's intentions to plagiarize an assignment. Moreover, the overall composite measure of detection did not prove statistically significant with overall plagiarism.

In analyzing the peer influences score, this variable proved significant with overall plagiarism, reaching a p-value below .01. Furthermore, this coefficient implies a positive relationship between peer influences and overall plagiarism likelihood. Specifically, when prior observations of peer cheating increases, the likelihood for plagiarism also increases.

Finally, the variables concerning costs & benefits all achieved significance at the .001 level. These values indicate that student perceptions of costs and benefits are quite influential on their likelihood to plagiarize. With positive coefficients across the three variables, this suggests that plagiarism is more likely to occur when it is beneficial to a student's academic success, peer relationships, and familial relationships. Furthermore, the results from costs & benefits composite measure demonstrate that overall perceptions of cheating benefits can impact student plagiarism.

Academic Dishonesty Overall

In examining the overall likelihood for academic dishonesty, all of the rational choice variables produced statistically significant coefficients at the .001 level. In regards to the reporting variables, formal reporting for test cheating, plagiarism, and homework cheating had a negative relationship with a student's overall likelihood to cheat. Similarly, the reporting composite score also produced a negative coefficient, which implies that the likelihood for academic dishonesty decreases as the likelihood for formal reporting increases. These results may suggest that fear of formal reporting can discourage academic dishonesty among students, providing direct support for this study's reporting hypothesis.

For the detection variables, similar results were also produced through this bivariate analysis. For each of the detection variables, a negative correlation coefficient was calculated. This indicates that as the likelihood for cheating detection increases, the likelihood of academic dishonesty decreases. Moreover, the results of this analysis would suggest that test cheating detection, plagiarism detection, and homework cheating detection all have a statistically significant and negative relationship with the overall likelihood for academic dishonesty. The results from these statistics further support this study's hypothesis that increases in cheating detection can decrease the overall rates of college student cheating.

For the peer influences variable, prior observations of peer cheating seemed to have a strong impact on a student's likelihood for academic dishonesty. Unlike the reporting and detection variables, a positive correlation coefficient was produced for this analysis. With a positive coefficient, this implies that academic dishonesty increases as the number of peer observations increase. More specifically, students who witnessed multiple forms of cheating seem to be at the higher risk for cheating engagement. In general, this was the expected outcome, as the dependent variable in this analysis is overall academic dishonesty. As such, witnessing different forms of peer cheating should be associated with increases in the overall academic dishonesty composite score.

Similar to the test cheating and plagiarism analyses, perceptions of costs & benefits seem to be quite influential on overall academic dishonesty. With correlation values close to .500, this suggests that student perceptions of cheating costs have the strongest associations with overall cheating. More precisely, academic dishonesty appears less likely when engagement in these actions provide harsher costs to a student's academic success, peer relationships, and familial relationships. In combination with the previous findings, these correlation coefficients provide strong evidence that student perceptions of cheating costs and benefits are quite relevant within studies of academic dishonesty. Furthermore, this evidence supports the use of rational choice theory as an underlying framework for college student cheating research.

Multivariate Analysis

While bivariate analyses provide preliminary information concerning the relationships between independent and dependent variables, the results are limited. Specifically, the previous bivariate tests examine the singular association between an independent variable and dependent variable. Use of multivariate statistics allow for multiple independent variables within each

model. By including a number of independent variables within each multivariate model, relationships between independent and dependent variables can be better assessed.

In preparing for multivariate testing, each of the independent variables in this study were carefully assessed. Upon examination of these variables, the age variable and the GPA variable were recoded for this form of quantitative analysis. For age, respondents within the upper ages were collapsed and recoded into a single group: 28 years old and older. While the majority of respondents were between the ages of 18 and 24, a minority of students reported ages above this range. To resolve issues concerning the distribution of ages (i.e., positive skew), the small proportion of older students were recoded into one age group. The age variable still will be expressed as a continuous variable. GPA, on the other hand, underwent a more significant recoding for multivariate analysis.

The GPA variable was changed to a dichotomous measure, whereby students were separated into a "3.50 – 4.00" group and a "lower than 3.50" group. As presented in the descriptive statistics, the majority of respondents identified their GPA as 3.50 or higher. Tamhane's post hoc analyses performed on the five GPA groups further indicate that these "A" students appeared to have the most notable distinctions for lesser academic dishonesty intentions. Furthermore, cheating intentions among the bottom four GPA groups appeared quite similar based on these post-hoc analyses. As such, transforming the GPA variable into a dichotomous variable appeared appropriate. Overall, assessments for all other independent variables indicated suitability for multivariate testing within their current forms. As such, only age and grade point average required coding revisions within this analysis.

Logistic Regression

In this study, academic dishonesty initially was measured based on nine dependent variables. For each dependent variable, two logistic regression models were produced. In each

corresponding table, the first logistic regression model examined the impact of seven demographic variables on a student's likelihood of engaging in cheating. Specifically, the seven independent variables included course type (0 = traditional course, 1 = online course), student age, graduate status (0 = undergraduate student, 1 = graduate student), grade point average, student gender (0 = not a female, 1 = female), citizenship (0 = domestic student, 1 = international student), and academic major (0 = non-criminal justice major, 1 = criminal justice major). In addition to the demographic variables, the second logistic regression model introduced five perceptual variables: previous observations of peer test cheating (0 = no, yes = 1), the perceived likelihood of detection (a scale measure where 0 = 0% likelihood and 10 = 100% likelihood), perceived likelihood of formal reporting (a scale measure where 0 = 0% likelihood and 10 = 100% likelihood), perceptions of course quality (0 = very poor, 10 = excellent), and the composite measure of cheating costs & benefits (an average of the three costs & benefits variables). Overall, tables 14 through 22 present the logistic regression models for each cheating behavior.

Test Cheating (Copying)

In Table 14, Model 1, the impact of seven demographic variables on a student's likelihood of test copying was assessed through logistic regression analysis. Based on the results of this first logistic regression model, only three of these of demographic variables proved statistically significant in predicting a student's likelihood for test copying: course type, age, and grade point average. With respect to course type, the data suggest that students in online courses are more likely to engage in test copying. With an odds ratio of 1.57, this implies that when controlling for other variables, online students have 57% higher odds of potentially engaging in test copying. Moreover, these differences between traditional students and online students were significant at the .001 level. Similarly, age also was statistically significant at the .001 level. The

results suggest that as student age increases, the likelihood for test copying decreases. Specifically, with each one unit increase in age, the simple odds of potentially engaging in test copying are reduced by 10% when controlling for other variables. Lastly, students with a GPA higher than 3.50 appeared less likely to engage test copying. With an odds ratio of 0.73, this indicates that when controlling for other variables, “A” range students have 27% lower odds of potentially engaging in test copying.

Table 14

Logistic Regression for Test Cheating (Copying)

	Model 1			Model 2		
	B	SE	Exp(B)	B	SE	Exp(B)
Constant	**1.41***	.714	4.08	.516	.899	1.67
Course Type	**.451*****	.135	1.57	-.174	.165	0.84
Age	**-.104****	.034	0.90	-.066	.041	0.94
Graduate	-.128	.264	0.88	-.014	.303	0.99
GPA 3.50 – 4.00	**-.315***	.142	0.73	**-.502****	.167	0.61
Female	-.045	.149	0.96	-.008	.173	0.99
Citizenship	.285	.233	1.33	**.622***	.271	1.86
Major	.094	.181	1.10	**.415***	.209	1.51
Peer Exams				.219	.186	1.25
Test Cheating Detection				.011	.037	1.01
Test Cheating Reporting				**-.065***	.033	0.94
Quality				**-.119*****	.031	0.89
Costs & Benefits Composite				**.456*****	.036	1.58
Nagelkerke R^2	.053			.345		

*p ≤ .05 **p ≤ .01 ***p ≤ .001

In Model 2, five perceptual variables were added to the previously analyzed demographic variables. Once these variables were added to the logistic regression model, statistical significance for several of the demographic variables changed. While course type and age were statistically significant within the first model, these variables no longer retained significance in the second logistic model. GPA ($p \leq .01$), however, remained statistically significant in the second model, yielding the strongest p-value among the demographic variables. Moreover, two previously insignificant variables now achieved statistical significance: student citizenship and student academic major.

For student citizenship, the likelihood for test copying appears more pronounced among international students. Specifically, when controlling for other factors, being an international student was associated with 86% higher odds of potential test copying. Relatedly, test copying appeared more pronounced among criminal justice majors as well. When controlling for other factors, criminal justice majors had 51% higher odds of engaging in test copying. Overall, these findings indicate that course type and age are less important when considering perceptual variables among students, and that student perceptions appear to mediate the influence of course type and age in predicting the likelihood of test copying.

When looking at the five perceptual variables in Model 2, three of these variables proved statistically significant: likelihood for test cheating reporting ($p \leq .05$), perceptions of course quality ($p \leq .001$) and the overall perceptions of cheating costs & benefits ($p \leq .001$). For likelihood of test cheating reporting, the odds of test cheating copying decrease as the likelihood for formal reporting increases. More precisely, with each one unit increase in perceived likelihood of being formally reported for test cheating, the simple odds of engaging in test copying are reduced by 6% when controlling for other variables. With regard to course quality, the likelihood of test copying appears lower among students who are more satisfied with the

quality of education received. Specifically, when controlling for other variables, each one unit increase in perceived course quality reduces the odds of test cheating by 11%. For overall perceptions of cheating costs & benefits, test copying appears more likely when students view cheating as more beneficial to their academic success and peer/familial relationships. When controlling for other variables, each one unit increase in the perceived benefits of cheating increases the simple odds of test copying by 58%.

In looking at the first logistic regression model in Table 14, a Nagelkerke R^2 value of .053 was produced, suggesting a modest 5.3% explained variation in the dependent variable (or 94.7% unexplained variation). With a high unexplained variation, this indicates that key variables related to test copying are excluded. However, the second logistic regression model saw a drastic increase in the Nagelkerke R^2, which would imply that these perceptual variables are quite influential on the likelihood of student test copying. Model 2 yielded a Nagelkerke R^2 value of .345, corresponding to an estimated 34.5% explained variation. As such, in addition to individual characteristics, student perceptions appear quite relevant to the likelihood of test copying.

Test Cheating (Collusion)

In this study, the test cheating collusion variable measured student likelihoods for providing answers to a classmate during an examination. As shown in Table 15, several demographic and perceptual variables proved statistically significant for this form of test cheating. In the first model, course type proved significant at the .001, level while age achieved significance at the .01 level. For course type, the results suggest that the likelihood for test collusion is higher among online students. Specifically, the odds of an online student engaging in this form of cheating were 55% higher than traditional students. In analyzing the age variable, test cheating collusion had a negative relationship with age. Specifically, the likelihood for test

cheating collision decreases as student age increases. When controlling for other demographic variables, each one unit increase in age corresponds with 10% lower odds for collusion during an examination.

Table 15

Logistic Regression for Test Cheating (Collusion)

	Model 1			Model 2		
	B	SE	Exp(B)	B	SE	Exp(B)
Constant	**1.46***	.695	4.32	.786	.871	2.19
Course Type	**.439*****	.133	1.55	-.202	.162	0.82
Age	**-.104****	.033	0.90	-.068	.040	0.93
Graduate	-.124	.256	0.88	-.009	.295	0.99
GPA 3.50 – 4.00	-.048	.142	0.95	-.167	.164	0.85
Female	-.246	.145	0.78	-.291	.168	0.75
Citizenship	.307	.225	1.36	**.660****	.261	1.94
Major	-.009	.181	0.99	.265	.208	1.30
Peer Exams				**.415***	.182	1.51
Test Cheating Detection				-.036	.035	0.97
Test Cheating Reporting				-.059	.032	0.94
Quality				**-.099*****	.030	0.91
Costs & Benefits Composite				**.432*****	.035	1.54
Nagelkerke R^2	.043			.335		

*$p \leq .05$ **$p \leq .01$ ***$p \leq .001$

In the second logistic regression model, inclusion of the five perceptual variables resulted in notable changes among the demographic variables. First, course type and age no longer remained statistically significant within this second model. This loss of significance would suggest that course type and age are not as important to test collusion when other perceptual factors are considered. Interestingly, citizenship gained significance within this second logistic

regression model, with a p-value less than .01. This model indicates that the risk for test collusion is higher among international students. More precisely, when controlling for other factors, the odds of international students engaging in test collusion are 94% higher than among domestic students.

Finally, three of the perceptual variables appear to influence the likelihood for test collusion among college students: peer exams ($p \leq .05$), quality ($p \leq .001$), and overall costs & benefits ($p \leq .001$). For the peer exams variable, the likelihood for test collusion appears higher among students who have previously witnessed peer exam cheating. When controlling for other factors, these students have 51% higher odds for possible engagement in test collusion. In looking at the quality variable, student satisfaction with their education appears especially relevant to their likelihood of colluding on a test. For this variable, students reported the overall quality of education received within their respective courses. Based on the statistics presented in Table 15, higher student satisfaction with their courses decreased their likelihood for test collusion. When controlling for other factors, each one unit increase in perceived quality corresponds to 9% lower odds for test collusion. Lastly, the composite measure for perceived costs & benefits proved highly significant on a student's likelihood of test collusion. As shown in Table 15, students who consider academic dishonesty more beneficial are more likely to engage in this form of test cheating. The logistic regression model indicates that when controlling for other factors, each one unit increase in perceived cheating benefits result in 54% higher odds of test collusion engagement.

When analyzing the Nagelkerke R^2 values in both logistic regression models, the differences again are quite apparent. In the first model, a Nagelkerke R^2 value of .043 was generated. This value suggests that when using demographic variables within a logistic regression analysis, an explained variation level of 4.3% is achieved. Alternatively, inclusion of

the five perceptual variables resulted in a notable improvement in Nagelkerke R^2, generating a value of .335. This value indicates that through use of the second logistic regression, an estimated 33.5% of the variation in test collusion is achieved. As such, the second logistic regression model appears more appropriate when analyzing a student's likelihood for test cheating collusion.

Test Cheating (Advance)

The test cheating advance variable reflects a student's likelihood for receiving questions or answers from a classmate prior to an examination. In looking at Model 1 of Table 16, student age was the only demographic variable to achieve statistical significance within this logistic regression analysis. With a p-value less than .001, student age appears quite influential on a student's likelihood for receiving test questions or answers. More precisely, when controlling for other demographic variables, each one unit increase in student age corresponds to 11% lower odds for possible engagement in this form of test cheating.

Interestingly, when the perceptual variables were added in the second logistic regression model, p-values for several of the demographic variables changed. First, the significance level for age was reduced to the .05 level. Despite this lower significance level, the age variable still had a negative relationship with test cheating advance and the odds ratio remained relatively unchanged. Alternatively, Model 2 saw notable changes in the course type variable and the citizenship variable. For course type, the differences between traditional students and online students achieved significance at the .001 level. Specifically, online students appear less likely to receive questions or answers before an exam. When controlling for other factors, online students display 51% lower odds for test cheating advance than traditional students. For student citizenship, the differences between domestic students and international students were significant at the .05 level. The Model 2 statistics imply that international students are more likely to engage

in this form of test cheating. More precisely, international students display 68% higher odds of receiving exam questions or answers, when controlling for other factors.

Table 16

Logistic Regression for Test Cheating (Advance)

	Model 1			Model 2		
	B	SE	Exp(B)	B	SE	Exp(B)
Constant	**2.10****	.666	8.17	.846	.817	2.33
Course Type	-.073	.127	0.93	**-.715*****	.157	0.49
Age	**-.114*****	.032	0.89	**-.077***	.037	0.93
Graduate	-.128	.243	0.88	-.068	.278	0.93
GPA 3.50 – 4.00	-.060	.136	0.94	-.149	.155	0.86
Female	.060	.140	1.06	.095	.159	1.10
Citizenship	.176	.216	1.19	**.519***	.248	1.68
Major	-.042	.173	0.96	.174	.194	1.19
Peer Exams				**.477****	.176	1.61
Test Cheating Detection				.002	.033	1.00
Test Cheating Reporting				-.018	.030	0.98
Quality				**-.068***	.028	0.93
Costs & Benefits Composite				**.433*****	.035	1.54
Nagelkerke R^2	.047			.310		

*$p \leq .05$ **$p \leq .01$ ***$p \leq .001$

Among the perceptual variables, three proved significant on a student's likelihood to receive exam questions or answers: peer exams ($p \leq .01$), quality ($p \leq .05$), and costs & benefits ($p \leq .001$). The findings for peer exams indicate that students who had previously witnessed test cheating among their peers have a higher likelihood of engagement in this form of test cheating. When controlling for other variables, students with these prior observations have 61% higher odds for receiving exam questions and answers. For perceptions of quality and perceptions of

costs & benefits, the findings were similar to the logistic regression models for test cheating copy and test cheating collusion. For quality, students who expressed greater satisfaction in their education reported lower likelihoods for test cheating advance. When controlling for other factors, each one unit increase in perceived quality translates to 7% lower odds for this form of test cheating. For the composite measure of costs & benefits, students were more likely to receive exam questions and answers when they perceived higher rewards towards their academic, peer, and familial goals. The odds ratio indicates that each one unit increase in perceived benefits increases the simple odds for test cheating advance by 54%, when controlling for other variables.

In examining the Nagelkerke R^2 values for both logistic regression models, Model 2 again generated a stronger value. As previously mentioned, the Nagelkerke R^2 values are estimated measures of explained variation between the independent variables and the dependent variable. For statistical analysis, models with the higher R^2 values have stronger explanatory power. As shown in Table 16, the first logistic regression model achieved a Nagelkerke R^2 value of .047, corresponding to a 4.7% explained variation level. However, the second model achieved a Nagelkerke R^2 value of .310, which suggests 31% explained variation between the variables. As such, the second analysis (containing both the demographic and perceptual variables) can be considered a stronger model for explaining a student's likelihood for receiving exam questions or answers.

Test Cheating (Cribnotes)

For test cheating cribnotes, this variable reflects student likelihoods for using unauthorized notes during an examination. As shown in Table 17, Model 1, course type was the only demographic variable to achieve statistical significance, earning a p-value less than .001. This statistic indicates that when examining cribnotes use, significant differences exist between

traditional students and online students. More precisely, online students report higher likelihoods of engaging in this form of test cheating. When controlling for other demographic variables, the simple odds of using unauthorized notes during an exam were 349% higher (over 4 times higher) among online students. When introducing the five perceptual variables into the second logistic regression model, course type retained its significance at the .001 level. When controlling for both demographic and perceptual variables, the simple odds statistic was reduced to reflect a 273% increase in the simple odds of cribnote use. Furthermore, two other demographic variables gained significance within this second model.

Table 17

Logistic Regression for Test Cheating (Cribnotes)

	Model 1			Model 2		
	B	SE	Exp(B)	B	SE	Exp(B)
Constant	.205	.671	1.23	-1.58	.835	0.21
Course Type	**1.50*** **	.137	4.49	**1.32*** **	.165	3.73
Age	-.055	.032	0.95	.012	.037	1.01
Graduate	-.172	.248	0.84	-.149	.290	0.86
GPA 3.50 – 4.00	-.178	.143	.837	**-.370***	.168	0.69
Female	-.049	.147	.952	-.064	.174	0.94
Citizenship	-.216	.223	0.81	-.017	.265	0.98
Major	.128	.181	1.14	**.446***	.211	1.56
Peer Exams				.130	.198	1.14
Test Cheating Detection				-.036	.035	0.97
Test Cheating Reporting				**-.067***	.032	0.94
Quality				-.048	.030	0.95
Costs & Benefits Composite				**.524*** **	.039	1.69
Nagelkerke R^2	.172			.457		

*p ≤ .05 **p ≤ .01 ***p ≤ .001

As highlighted in Table 17, student grade point average and major both became significant at the .05 level. Specifically, these statistics suggest that notable differences exist among "A" grade students and criminal justice majors. For grade point average, students were grouped into two GPA groups: "3.50 – 4.00" and "3.49 and below." Model 2 reveals that students in the higher GPA group were less likely to use cribnotes during an exam. When controlling for other factors, these "A" students were 31% less likely to engage in this form of test cheating. For major, the second model suggests that criminal justice majors are more likely to use unauthorized notes during an exam. More precisely, criminal justice majors had 56% higher odds of using cribnotes while controlling for other factors.

Within the second model, the costs & benefits composite measure was the only perceptual variable to achieve a statistically significant p-value ($p \leq .001$). In general, this would imply that the likelihood for cribnotes use during an exam is highly influenced by a student's perceptions of cheating costs & benefits. As evidenced in Table 17, students reported a greater willingness to use unauthorized notes when cheating was perceived more rewarding to their academic, peer, and familial goals. When controlling for other factors, each one unit increase in perceived cheating benefits corresponded to 69% higher odds for cribnotes use among college students.

Finally, the Nagelkerke R^2 values for these logistic regression analyses are worth noting, as both models yielded impressive scores. More specifically, these models for test cheating cribnotes had the highest Nagelkerke R^2 values among the nine logistic regression analyses. For the first model, the demographic variables produced a Nagelkerke R^2 value of .172. This indicates that demographic variables alone provide 17.2% explained variation within the dependent variable. Comparatively, this is a high statistic, as the other eight Model 1's had explained variation levels below 10%. When both demographic and perceptual variables were

considered in Model 2, the Nagelkerke R^2 value increased to .457. This suggests that this second logistic regression model generated 45.7% explained variation in a student's likelihood of cribnote use.

Homework Collusion

For homework collusion, students reported their likelihood of collaborating on a homework assignment when it is not permitted by an instructor. As shown in Model 1 of Table 18, two demographic variables were statistically significant at the .05 level: student age and citizenship. According to the data, age appears to have a negative relationship with homework collusion, suggesting that older students are less likely to engage in this form of cheating. When controlling for other demographic variables, each one unit increase in age decreases the simple odds of homework collusion by 7%. Similarly, the likelihood for homework cheating appears lower among international students. With an odds ratio of 0.64, this implies that when controlling for other variables, international students have 36% lower odds of potentially engaging in homework cheating. In looking at the second logistic regression model, however, changes to these variables occurred.

The second logistic regression model added five perceptual variables to the analysis. In doing so, the age and citizenship variables no longer remained statistically influential on the likelihood for homework collusion. This would suggest that student age and citizenship are not as important to homework collusion when perceptual factors are considered, or that the perceptual variables are mediating the effects of age and citizenship. Additionally, this second logistic regression model saw a change in significance for grade point average. While grade point average was previously insignificant in Model 1, the p-value became significant at the .05 level in Model 2. This analysis indicates that the likelihood for homework cheating is lower among students with a 3.50 to 4.00 grade point average. Moreover, when controlling for other

variables, students in this GPA range are 30% less likely to engage in this form of academic dishonesty.

Table 18

Logistic Regression for Homework Collusion

	Model 1			Model 2		
	B	SE	Exp(B)	B	SE	Exp(B)
Constant	**1.94****	.632	6.98	**.149****	.794	1.16
Course Type	-.027	.125	0.97	-.427	.161	0.65
Age	**-.077***	.030	0.93	-.018	.036	0.98
Graduate	-.207	.230	0.81	-.209	.277	0.81
GPA 3.50 – 4.00	-.106	.135	0.90	**-.354***	.161	0.70
Female	-.112	.138	0.89	-.243	.165	0.78
Citizenship	**-.444***	.207	0.64	-.154	.249	0.86
Major	-.050	.169	0.95	.174	.199	1.19
Peer Homework				**1.34*****	.174	3.81
Homework Detection				-.016	.035	0.98
Homework Reporting				-.056	.033	0.95
Quality				-.033	.029	0.97
Costs & Benefits Composite				**.466*****	.037	1.59
Nagelkerke R^2	.061			.404		

$^*p \leq .05$ $^{**}p \leq .01$ $^{***}p \leq .001$

Among the perceptual variables included in Model 2, peer homework and the costs & benefits composite measure proved statistically significant at the .001 level. For peer homework, students reported prior observations of peer homework cheating within their respective courses. Based on the data, students who had previously observed peer homework cheating were more willing to engage in similar behaviors. The odds ratio indicates that students with such prior

observations had 281% higher (nearly 4 times higher) odds of engaging in homework cheating, when controlling for other factors. Perceptions of costs & benefits also proved important in explaining student likelihood for homework cheating. Students who considered academic dishonesty more beneficial to their personal goals again expressed higher likelihoods for homework collusion. When considering other demographic and perceptual variables, each one unit increase in perceived cheating benefits increased the simple odds of homework cheating by 59%.

As shown in Table 18, the two logistic regression models yielded interesting Nagelkerke R^2 values. For the demographic variables in Model 1, the Nagelkerke R^2 value was .061, which equates to a 6.1% explained variation level for homework cheating. However, Model 2 for homework collusion saw a notable spike in Nagelkerke R^2, with a value of .404. When compared to other Model 2 results, the homework collusion model generated one of the higher R^2 values. This implies that use of this logistic regression model can explain roughly 40% of the variation in homework collusion. This dramatic difference between these two homework models would also suggest that peer observations and perceived cheating costs & benefits are highly influential to a student's likelihood for homework cheating.

Plagiarism (Collusion)

The plagiarism collusion variable measured a student's likelihood of submitting a paper that was partially or completely written by someone else. In Model 1 of Table 19, three of the demographic variables proved statistically significant at the .001: grade point average, female, and citizenship. For grade point average, students with grade point averages higher than 3.50 had a lower likelihood for engaging in plagiarism collusion. When controlling for other factors, students in this GPA group had 52% lower odds for this form of cheating. Similarly, females displayed a lower likelihood for this type of plagiarism. Specifically, females had 49% lower

odds for plagiarism collusion when considered alongside other variables. Lastly, citizenship proved especially important within this logistic regression model. Based on these statistics, international students displayed a higher likelihood for plagiarism collusion. The odds ratio indicates that international students are 178% more likely to engage in this form of plagiarism when controlling for other factors.

Table 19

Logistic Regression for Plagiarism (Collusion)

	Model 1			Model 2		
	B	SE	Exp(B)	B	SE	Exp(B)
Constant	-.876	.867	0.42	**-2.33***	1.03	0.10
Course Type	.172	.173	1.19	-.198	.196	0.82
Age	-.014	.042	0.99	.029	.048	1.03
Graduate	-.039	.331	0.96	.024	.356	1.03
GPA 3.50 – 4.00	**-.730*****	.182	0.48	**-.843*****	.200	0.43
Female	**-.672*****	.178	0.51	**-.763*****	.195	0.47
Citizenship	**1.02*****	.268	2.78	**1.22*****	.295	3.38
Major	.128	.244	1.14	.392	.264	1.48
Peer Plagiarism				**.619***	.285	1.86
Plagiarism Detection				-.048	.043	0.95
Plagiarism Reporting				-.026	.041	0.98
Quality				.006	.036	1.01
Costs & Benefits Composite				**.372*****	.039	1.45
Nagelkerke R^2	.093			.264		

*p ≤ .05 **p ≤ .01 ***p ≤ .001

In general, Model 2 echoed the findings from Model 1. More precisely, the three previously identified demographic variables remained statistically significant at the .001 level, confirming the odds of potential plagiarism collusion were lower among “A” grade students,

females, and domestic students. While the odds ratios remained relatively similar for the GPA and female variables, citizenship saw a notable increase. Specifically, when controlling for both demographic and perceptual factors, international students had 238% higher odds of engaging in plagiarism collusion.

Among the newly introduced perceptual variables, two achieved statistical significance: prior observations of peer plagiarism ($p \leq .05$) and perceptions of costs & benefits ($p \leq .001$). For the peer plagiarism variable, students who had previously witnessed plagiarism among their peers were more likely to potentially engage in plagiarism themselves. Specifically, the odds are 86% higher for these students when compared against those with no prior observations of plagiarism. It is also worth noting that this peer variable produced the weakest p-value among the five statistically significant variables in the second logistic regression model. As such, the impact of peer observations on plagiarism collusion may be more limited when compared to these other variables. Finally, the costs & benefits composite measure proved highly influential on a student's likelihood for plagiarism collusion. For students who perceived cheating as more beneficial, possible engagement in this form of plagiarism is higher. Specifically, for each one unit increase in perceived cheating benefits, the odds of plagiarism collusion increased by 45%. In general, these findings suggest that both demographic and perceptual variables have important influences on a student's likelihood for plagiarism collusion.

In looking at the overall findings from both logistic regression models, Model 1 yielded a Nagelkerke R^2 value of .093, corresponding to a 9.3% explained variation level. When perceptual variables were added to the demographic variables in Model 2, the Nagelkerke R^2 value increased to .264, which indicates an improved explained variation level of 26.4%. This improved explained variation level would imply that the second logistic regression model is more appropriate in measuring the likelihood of plagiarism collusion.

Plagiarism (Material)

For the plagiarism material variable, students reported their likelihood of plagiarizing public material within a course paper. When analyzing the logistic regression models for plagiarism material, the findings were quite similar to plagiarism collusion. For both plagiarism collusion and plagiarism material, a student's grade point average, gender, and citizenship achieved statistical significance in both logistic regression analyses. However, the levels of significance are a notable distinction within the plagiarism material models. As shown in Table 20, the p-values for these three variables were different within both the demographic regression model and the demographic/perceptual regression model. In Model 1, student gender and grade point average were significant at the .05 level, while citizenship earned a p-value of less than .001. When controlling for other demographic variables, "A" range students have 40% lower odds of engaging in this form of plagiarism, while females have 34% lower odds for the same behavior. Conversely, citizenship proved the most significant among the demographic variables, with international students having 154% higher odds of plagiarizing public material, when considered alongside other individual factors.

When adding the perceptual variables to the logistic regression model, the results remained relatively unchanged for these three demographic variables. Particularly, the female and citizenship variables retained their significance levels, while the GPA variable shifted from the .05 significance level to the .01 significance level. The odds ratios also remained relatively unchanged for both the GPA variable and the female variable. The most apparent change to the odds ratio occurred within the citizenship variable. When controlling for both demographic and perceptual factors, international students had 221% higher odds of potentially plagiarizing public material.

Table 20

Logistic Regression for Plagiarism (Material)

	Model 1			Model 2		
	B	SE	Exp(B)	B	SE	Exp(B)
Constant	-.468	.804	0.63	-1.40	.954	0.25
Course Type	.223	.159	1.25	-.201	.181	0.82
Age	-.036	.039	0.97	.001	.044	1.00
Graduate	.186	.300	1.20	.359	.324	1.43
GPA 3.50 – 4.00	**-.507***	.168	0.60	**-.587****	.185	0.56
Female	**-.416***	.166	0.66	**-.426***	.183	0.65
Citizenship	**.931*****	.243	2.54	**1.17*****	.269	3.21
Major	-.073	.231	0.93	.182	.250	1.20
Peer Plagiarism				.270	.274	1.31
Plagiarism Detection				-.049	.040	0.95
Plagiarism Reporting				-.044	.038	0.96
Quality				-.046	.032	0.96
Costs & Benefits Composite				**.372*****	.037	1.45
Nagelkerke R^2	.070			.258		

*p ≤ .05 **p ≤ .01 ***p ≤ .001

When analyzing the five perceptual variables in the logistic regression model, the composite measure for perceived costs & benefits was the only variable to achieve statistical significance. With a p-value less than .001, this suggests that perceptions of costs & benefits are influential on a student's likelihood for plagiarism material. Specifically, students who consider cheating more beneficial are more likely to engage in this form of plagiarism. As shown in the second model for Table 20, each one unit increase in perceptions of benefits increases a student's odds of plagiarizing public material by 45%.

In addition to these statistics, the Nagelkerke R^2 values are also worth noting. In the first logistic regression model for plagiarism material, a Nagelkerke R^2 value of .070 was produced. This indicates that the combination of demographic variables provide 7% explained variation in a student's likelihood for plagiarizing public material. Furthermore, inclusion of the perceptual variables led to an increase in Nagelkerke R^2 of .258. This implies that use of the second logistic regression explains roughly 26% of the variation in student intentions to plagiarize public material.

Plagiarism (Padding)

When analyzing student intentions to pad a bibliography, several demographic and perceptual variables proved statistically significant in the two logistic regression models. As shown in Table 21, two demographic variables proved significant in the first model: age ($p \leq .05$) and grade point average ($p \leq .01$). When looking at age, this variable had a negative relationship with the likelihood for plagiarism padding. Specifically, increases in age correspond with lower likelihoods for this form of plagiarism. When controlling for other demographic factors, each one unit in age increases the simple odds of potential plagiarism padding by 6%. For grade point average, the likelihood of padding a paper was lower among the "A" grade students. More precisely, these students displayed 31% lower odds for plagiarism padding when controlling for other variables.

In examining the second logistic regression model, minor changes occurred among the demographic variables. The second model again provided the addition of five perceptual variables into the regression analysis. As a result of these added variables, age was no longer statistically significant. Alternatively, the variable for course type became significant at the .05 level, suggesting that online students had a lower willingness to pad a paper. When controlling for other factors, the simple odds of plagiarism padding were 27% lower among online students.

For the GPA variable, the differences were minimal between the first and second model. In the second model, grade point average remained significant at the .01 level and retained a similar odds ratio within logistic analysis.

Table 21

Logistic Regression for Plagiarism (Padding)

	Model 1			Model 2		
	B	SE	Exp(B)	B	SE	Exp(B)
Constant	1.08	.666	2.94	-.047	.781	0.95
Course Type	.125	.129	0.94	**-.311***	.150	0.73
Age	**-.066***	.032	0.94	-.024	.036	0.98
Graduate	.087	.245	1.09	.143	.268	1.15
GPA 3.50 – 4.00	**-.372****	.138	0.69	**-.481****	.152	0.62
Female	-.229	.141	0.80	-.227	.154	0.80
Citizenship	.088	.214	1.09	.263	.237	1.30
Major	.066	.175	1.07	.265	.191	1.30
Peer Plagiarism				.313	.240	1.37
Plagiarism Detection				-.018	.033	0.98
Plagiarism Reporting				-.015	.031	0.99
Quality				**-.055***	.027	0.95
Costs & Benefits Composite				**.362*****	.032	1.44
Nagelkerke R^2	.025			.225		

*p ≤ .05 **p ≤ .01 ***p ≤ .001

For the perceptual variables, two proved statistically significant within the second model: perceptions of quality ($p \leq .05$) and overall perceptions of costs & benefits ($p \leq .001$). For perceptions of quality, this variable again had a negative relationship with plagiarism padding. Specifically, as student perceptions of quality increase, the likelihood for padding a paper decreases. An odds ratio of 0.95 indicates that each one unit increase in quality decreases the

simple odds of student paper padding by 5%, when controlling for other factors. The composite measure for perceived cheating costs & benefits appears highly influential on plagiarism padding, earning the most significant p-value among the independent variables. Overall, students appear more likely to pad a paper when academic dishonesty is viewed more beneficially. When controlling for other variables, each one unit increase in perceived cheating benefits increased the simple odds of student plagiarism padding by 44%.

In analyzing the Nagelkerke R^2 values, the first and second logistic regression models for plagiarism padding produced statistics of .025 and .225 respectively. In general, the .225 Nagelkerke R^2 value would imply that the second logistic regression model is more appropriate for analyzing student likelihoods for paper padding. Moreover, use of the demographic and perceptual variables in Model 2 generated 22.5% explained variation in student odds for plagiarism padding. However, this value is rather low when compared to the Nagelkerke R^2 values in the other logistic regression models containing both demographic and perceptual variables. This lower value would indicate that when looking at student likelihoods for plagiarism padding, relevant independent variables are being excluded from the logistic regression model.

Plagiarism (Copy)

The final logistic regression model within this study examined student likelihoods of copying sentences into papers without citing the source. For the first model, seven demographic variables were included within the logistic regression analysis. Among these variables, both the GPA variable and female variable achieved statistical significance at the .05 level. For grade point average, this would imply that the difference in plagiarism copying is significant between the “A” grade students and the rest of the student population. Specifically, the data implies that students with a grade point average higher than 3.50 are less likely to engage in this form of

plagiarism. When controlling for other variables, these students displayed 29% lower odds for plagiarism padding. Similarly, significant differences exist between female and non-female students. In this study, female students reported lower likelihoods for plagiarism copying. In the first logistic regression model, an odds ratio of 0.73 was produced. This indicates that when controlling for other demographic factors, the simple odds of plagiarism copying are 27% lower among female students.

Table 22

Logistic Regression Plagiarism (Copy)

	Model 1			Model 2		
	B	SE	Exp(B)	B	SE	Exp(B)
Constant	.838	.675	2.31	-.447	.777	0.64
Course Type	-.086	.131	0.92	**-.512*** **	.151	0.60
Age	-.058	.032	0.94	-.023	.036	0.98
Graduate	.289	.248	1.34	.397	.268	1.49
GPA 3.50 – 4.00	**-.350***	.140	0.71	**-.447****	.153	0.64
Female	**-.313***	.141	0.73	**-.325***	.153	0.72
Citizenship	.331	.210	1.39	**.566***	.231	1.76
Major	.114	.178	1.12	.307	.192	1.36
Peer Plagiarism				.155	.239	1.17
Plagiarism Detection				.050	.034	1.05
Plagiarism Reporting				-.050	.031	0.95
Quality				-.033	.027	0.97
Costs & Benefits Composite				**.336*****	.032	1.40
Nagelkerke R^2	.026			.195		

*p ≤ .05 **p ≤ .01 ***p ≤ .001

The second logistic regression model in Table 22 saw the introduction of five perceptual variables into logistic analysis. In several of the previous logistic regression tables, adding these perceptual variables caused many demographic variables to lose significance. In this case,

however, GPA and female were significant in both models. Moreover, GPA improved in its significance level in the second model, generating a p-value less than .01. Other than this change, both the GPA and female variables remained relatively unchanged in the second analysis. More precisely, both models indicated plagiarism copying as less likely among the 3.50 – 4.00 grade students and female students. Also, the odds ratios remained relatively similar within the second logistic regression output. Beyond these changes, two demographic variables also became significant within the second model: course type ($p \leq .001$) and citizenship ($p \leq .05$). For course type, the statistics suggest that online students were less likely to engage in plagiarism copying than traditional students. When controlling for demographic and perceptual factors, the simple odds of copying sentences into a paper were 40% lower among online students. In analyzing the citizenship variable, the likelihood for plagiarism copying appeared higher among international students. Specifically, the odds of an international student engaging in this form of plagiarism are 76% higher when controlling for other variables. These gains in significance would indicate that course type and citizenship are highly influenced by perceptual factors.

Among the perceptual factors in Model 2, the costs & benefits composite measure was the only variable to achieve statistical significance. More accurately, the overall costs & benefits score produced a p-value less than .001. Consistent with the previous logistic regression models, students who consider cheating more beneficial to their academic, peer, and familial goals expressed a greater willingness to copy sentences into a paper. When controlling for other factors, each one unit increase in perceived cheating benefits increased the simple odds of plagiarism copying by 40%.

Finally, Table 22 highlights the Nagelkerke R^2 values for both logistic regression models pertaining to plagiarism copying. For the first model, which contained the demographic variables, the Nagelkerke R^2 value was .026. The second model, which contained both

demographic and perceptual variables, produced a Nagelkerke R^2 value of .195. In general, this would imply that the second logistic regression model provides greater explained variation at 19.5%. However, both models in Table 22 produced noticeably lower Nagelkerke R^2 values when compared to the previous logistic regression analyses. When comparing the second models for the nine dependent variables, the plagiarism copying model scored the lowest Nagelkerke R^2 value. This would indicate that the independent variables within this study do a poorer job at explaining a student's likelihood for copying sentences into a paper.

Negative Binomial Regression

In addition to the logistic regression models conducted for the nine cheating variables, negative binomial regression models were used to assess composite measures of the dependent variables. The nine dichotomous cheating variables were used to create count variables reflecting overall test cheating, overall plagiarism, and overall academic dishonesty.

The first composite measure examined responses concerning exam cheating. In the survey, students reported their likelihoods for engaging in four different actions related to test cheating. These data were coded as dichotomous dependent variables, where "0 = no likelihood" and "1 = possible likelihood" of academic dishonesty. To conduct further statistical testing, these four test cheating variables were combined into a single composite measure. For this variable, test cheating was expressed as a count variable ranging from 0 to 4. For example, students with a composite score of 0 disclosed no possibility of engaging in any of the test cheating behaviors. Alternatively, students with a composite score of 4 expressed a possible likelihood of engaging in all four forms of test cheating.

Similar to the test cheating composite score, a composite measure for the overall likelihood of plagiarism was created. In this study, four dichotomous variables were used to measure plagiarism behaviors among participants. These four measures were then combined into

a single count variable, scaled 0 to 4, which reflects how many forms of plagiarism a student potentially would pursue. With respect to coding, students with a 0 score expressed no likelihood of engaging in any form of plagiarism. Alternatively, students with any other composite score potentially would engage in at least one form of plagiarism.

Lastly, a total composite measure for overall academic dishonesty was utilized. As previously stated, participants reported their likelihood for engaging in various forms of test cheating, plagiarism, and homework cheating. Unlike the previous composite measures that strictly examined test cheating behaviors of plagiarism behaviors, the overall cheating variable reflects a student's general likelihood for engaging in any form of academic dishonesty. In this study, nine forms of test cheating, plagiarism, and homework cheating were identified and measured dichotomously. As such, the overall cheating variable is measured on a count of 0 to 9. In general, this variable represents a raw number of how many cheating behaviors a student potentially may pursue within a college course.

Overall Test Cheating

Table 23 presents a negative binomial regression model for overall intentions to test cheat. For this analysis, the composite score for test cheating served as the dependent variable. Among the variables included in Table 23, only two were statistically significant: quality perceptions ($p \leq .001$) and the costs & benefits composite measure ($p \leq .001$). In general, this model suggests that the log counts for test cheating are influenced significantly by a student's perceptions of course quality and how beneficial cheating appears to a student's academic, peer, and familial goals. When analyzing the quality variable, higher satisfaction with a course decreases the risk for test cheating engagement. Based on the incidence rate ratio shown in the Exp(B) column, when controlling for other variables, each one unit increase in perceived course quality is associated with a 6% reduction in the average count for test cheating engagement. In

comparison, the costs & benefits composite measure has a positive relationship with overall test cheating. Specifically, each one unit increase in perceived cheating benefits increases the average test cheating count by 28%, when controlling for other variables. While only two variables proved significant in this overall test cheating model, a larger number of independent variables achieved significance in the subsequent overall plagiarism model.

Table 23

Negative Binomial Regression for Overall Test Cheating

	B	SE	Exp(B)
Constant	**.945***	.475	2.57
Age	-.035	.021	0.97
Graduate	-.043	.164	0.96
GPA 3.50 – 4.00	-.169	.091	0.84
Female	-.035	.094	0.97
Citizenship	.165	.146	1.18
Course Type	-.001	.090	1.00
Major	.170	.115	1.18
Peer Exams	.142	.102	1.15
Test Cheating Detection	-.014	.020	0.99
Test Cheating Reporting	-.033	.018	0.97
Quality	**-.058*****	.017	0.94
Costs & Benefits Composite	**.249*****	.018	1.28

*p ≤ .05 **p ≤ .01 ***p ≤ .001

Overall Plagiarism

Similar to Table 23, Table 24 presents a negative binomial regression for overall plagiarism intentions. Within this regression analysis, four variables achieved significance:

citizenship ($p \leq .05$), grade point average ($p \leq .01$), female ($p \leq .01$), and the costs & benefits composite measure ($p \leq .001$). For citizenship, international students appear more likely to engage in plagiarism actions. More precisely, the incidence rate ratio shown in the Exp(B) column indicates the average count for plagiarism is 42% higher among international students, while controlling for other factors. For the grade point average variable, students with a GPA above 3.50 are significantly less likely to engage in plagiarism. When controlling for other variables, average plagiarism counts were 26% lower among these students. Similarly, this model suggests that female students were also less likely to engage in plagiarism, when compared to non-female students. The incident rate ratio indicates that the average count for plagiarism is 23% lower among female students, when considered alongside other factors. Lastly, the benefits composite measure proved especially significant within this regression model. This model reveals that the overall benefits variable has a positive relationship with intentions to plagiarize. Specifically, plagiarism intentions are higher among students who consider cheating to be more beneficial. When controlling for other factors, each one unit increase in perceived cheating benefits increases the average plagiarism count by 25%.

Table 24

Negative Binomial Regression for Overall Plagiarism

	B	SE	Exp(B)

Constant	.337	.493	1.40
Age	-.015	.023	0.99
Graduate	.194	.171	1.22
GPA 3.50 – 4.00	**-.304****	.097	0.74
Female	**-.263****	.097	0.77
Citizenship	**.350***	.146	1.42
Course Type	-.167	.095	0.85
Major	.178	.125	1.20
Peer Plagiarism	.201	.147	1.22
Plagiarism Detection	-.008	.021	0.99
Plagiarism Reporting	-.028	.020	0.97
Quality	-.033	.018	0.97
Costs & Benefits Composite	**.225*****	.019	1.25

*p ≤ .05 **p ≤ .01 ***p ≤ .001

Overall Academic Dishonesty

For the third negative binomial regression model, the total composite measure for overall cheating was used as the dependent variable. In looking at Table 25, four variables achieved statistical significance within the model: grade point average ($p \leq .01$), perceptions of quality ($p \leq .01$), the peer influences composite ($p \leq .01$), and perceptions of cheating costs & benefits ($p \leq .001$). Similar to the test cheating and plagiarism models in Table 23 and Table 24, students in the higher GPA group and students with higher perceptions of course quality expressed lower likelihoods for overall cheating behaviors. When controlling for other variables, the average counts for overall cheating were 19% lower among students with a GPA of 3.50 or higher. For

the quality variable, each one unit increase in perceived course quality reduced the average counts for cheating by 4%, when controlling for other factors.

Table 25

Negative Binomial Regression for Overall Academic Dishonesty

	B	SE	Exp(B)
Constant	**1.44******	.406	4.23
Age	-.023	.018	0.98
Graduate	.025	.141	1.03
GPA 3.50 – 4.00	**-.208****	.080	0.81
Female	-.126	.081	0.88
Citizenship	.180	.124	1.20
Course Type	-.083	.078	0.92
Major	.166	.101	1.18
Peer Influences	**.130****	.041	1.14
Detection	-.015	.023	0.99
Reporting	-.028	.020	0.97
Quality	**-.046****	.015	0.96
Costs & Benefits Composite	**.238*****	.016	1.27

*p ≤ .05 **p ≤ .01 ***p ≤ .001

Unlike the negative binomial models for overall test cheating and overall plagiarism, the overall cheating model included a total composite measure for peer influences. This composite measure reflected how many forms of academic dishonesty a student had observed among their peers. As shown in Table 25, students with higher counts for observed peer cheating expressed greater likelihoods for academic dishonesty. When controlling for other factors, each one unit

increase in peer cheating observations led to 14% higher average counts for academic dishonesty. Lastly, the costs & benefits composite measure proved highly significant in predicting student cheating intentions. For each one unit increase in perceived cheating benefits, the average counts for academic dishonesty increase by 27%, when controlling for other variables. Overall, the results of this model would suggest that both demographic and perceptual variables have an influence on a student's likelihood for academic dishonesty.

Negative Binomial Regression Split Models

In addition to the full negative binomial models presented above, a series of split models were created using negative binomial regression. In splitting a model, participants are separated based on certain characteristics identified within the data. In this study, examining the behavioral differences between traditional and online students, and between criminal justice and non-criminal justice majors, has been a central focus. As such, the first series of split models separated students based on course type, with the first model representing traditional students and the second model representing online students. Additionally, another set of split models were created based on academic major. For these models, students were separated into a "non-criminal justice major" group and a "criminal justice major" group. Through use of these split models, distinctions between groups can be more fully identified.

Course Type & Overall Test Cheating

In the first split model, differences in overall test cheating were examined based on course type. As shown in Table 26, the differences between traditional students and online students appear minimal within the context of overall test cheating. In both models, perceptions of quality and perceptions of cheating costs & benefits achieved statistical significance. For both traditional and online students, perceptions of quality was significant at the .05 level, while the overall costs & benefits measure was significant at the .001 level. Furthermore, z-scores were

calculated to test for the equality of regression coefficients across the two models (Clogg et al., 1995; Paternoster et al., 1998). Calculation of a significant z-score (i.e., greater than 1.96) would indicate a significant difference in independent variable slopes across the models for traditional and online student settings. As evidenced by the z-scores, the differences in slopes are insignificant for both the quality variable and the costs & benefits variable, along with the other independent variables included within the models.

Table 26

Split Model Negative Binomial Regression (Course Type & Overall Test Cheating)

	Traditional Setting			Online Setting			
	B	SE	Exp(B)	B	SE	Exp(B)	Z
Constant	1.67	.933	5.29	.980	.752	2.67	0.58
Age	-.061	.034	0.94	-.018	.029	0.98	0.96
Graduate	-.066	.248	1.07	-.019	.222	1.02	0.14
GPA 3.50 – 4.00	-.161	.135	1.17	-.151	.126	1.16	0.05
Female	-.012	.136	1.01	-.024	.131	1.02	0.06
Citizenship	.062	.223	0.94	.242	.195	0.76	0.61
Major	.162	.159	0.85	.173	.170	0.84	0.05
Peer Exams	.070	.158	0.93	.257	.137	0.77	0.89
Test Cheating Detection	-.040	.030	0.96	.006	.029	1.01	1.10
Test Cheating Reporting	-.033	.027	0.97	-.035	.026	0.97	0.05
Quality	**-.063***	.027	0.94	**-.056***	.023	0.95	0.20
Costs & Benefits Composite	**.281*****	.028	1.33	**.224*****	.024	1.25	1.55

$*p \leq .05$ $**p \leq .01$ $***p \leq .001$

Course Type & Overall Plagiarism

When analyzing the split models for overall plagiarism, differences between traditional students and online students were more apparent. Specifically, certain variables proved significant to traditional students, while others were significant among online students. For traditional students, academic major was significant at the .05 level. The data suggest that criminal justice majors are more likely to engage in plagiarism behaviors in traditional courses. When controlling for other variables, criminal justice majors had 31% higher average counts for plagiarism engagement in traditional courses. Within online courses, academic major was not significant in predicting overall plagiarism behaviors. Instead, the variables for grade point average, citizenship, and peer plagiarism observations achieved significance within online courses.

In the online class setting, intentions to plagiarize were significantly lower among students with a GPA of 3.50 or higher ($p \leq .05$). For these “A” students, the average counts for plagiarism were 36% lower than students with other GPA’s. For the citizenship variable ($p \leq .01$), intentions to plagiarize were higher among international students in online courses. Specifically, online international students had 10% higher average counts for plagiarism than domestic students in the same course setting, when controlling for other factors. Finally, prior observations of peer plagiarism ($p \leq .01$) appear quite influential among online students. For these students, personally witnessing peer plagiarism increases their own likelihood for plagiarism. When controlling for other variables, online students with these previous observations of peers had 40% higher average counts for plagiarism.

Table 27

Split Model Negative Binomial Regression (Course Type & Overall Plagiarism)

	Traditional Setting			Online Setting			
	B	SE	Exp(B)	B	SE	Exp(B)	Z
Constant	.384	.921	1.47	.629	.859	1.88	0.19
Age	-.020	.034	0.98	-.011	.031	0.99	0.20
Graduate	.271	.245	0.76	.146	.245	0.86	0.36
GPA 3.50 – 4.00	-.230	.140	1.26	**-.306***	.138	1.36	0.39
Female	-.236	.137	1.27	-.247	.140	1.28	0.06
Citizenship	.098	.217	0.91	**.532****	.200	1.10	1.52
Major	**.368***	.164	0.69	-.093	.200	1.10	1.78
Peer Plagiarism	-.254	.239	1.29	**.511***	.195	0.60	**2.48***
Plagiarism Detection	-.031	.031	0.97	.010	.030	1.01	0.95
Plagiarism Reporting	-.015	.030	0.99	-.034	.029	0.97	0.46
Quality	-.042	.028	0.96	-.023	.024	0.98	0.52
Costs & Benefits Composite	**.293*****	.030	1.34	**.172*****	.025	1.19	**3.10****

*p ≤ .05 **p ≤ .01 ***p ≤ .001

Furthermore, the z-score for the peer plagiarism variable also reached statistical significance at the .05 level. This indicates that the impact of peer plagiarism was significantly different between traditional students and online students. This statistic further indicates that peer plagiarism is particularly influential among online students. In general, this seems surprising, given the nature of online courses. Within online courses, students traditionally have had limited interactions with fellow peers. As such, personally witnessing peer plagiarism behaviors should

prove more difficult within an online course. During the Covid-19 pandemic, however, student interactions with online peers may have been more frequent than in previous times.

When comparing both models for traditional courses and online courses, the costs & benefits composite measure proved highly significant. More precisely, this costs & benefits variable earned a p-value less than .001 in both regression analyses. In general, increases in perceived cheating benefits increased a student's likelihood for plagiarism. For traditional students, each one unit increase in benefits resulted in 34% higher average counts for plagiarism, when controlling for factors. For online students, this incidence rate ratio was slightly lower, showing an estimated 19% increase in the average count. However, examination of the z-score for costs & benefits reveals a significant difference between the slopes for the two groups. As shown in Table 27, the z-score for the benefits variable was significant at the .01 level. When looking at these results, traditional students appear to be more impacted by perceptions of cheating costs & benefits than online students.

Course Type & Overall Academic Dishonesty

In examining overall cheating behaviors among traditional students and online students, certain disparities exist among variables, as shown in Table 28. For traditional students, the detection composite score was significant at the .05 level. This statistic indicates that increases in perceived cheating detection result in lower likelihoods for cheating engagement among traditional students. When controlling for other factors, each one unit increase in perceptions of cheating detection decrease the average counts for total cheating by 6%. Furthermore, the z-score for the detection composite variable was significant at the .05 level. This suggests that the slopes for cheating detection are different between traditional students and online students. More accurately, perceptions of cheating detection appear more influential among traditional students.

In general, this finding seems logical, as certain forms of cheating are more easily detected within physical settings than in remote settings.

Table 28

Split Model Negative Binomial Regression (Course Type & Overall Academic Dishonesty)

	Traditional Setting			Online Setting			
	B	SE	Exp(B)	B	SE	Exp(B)	Z
Constant	**1.83***	.764	6.25	1.19	.682	3.28	0.62
Age	-.041	.028	0.96	-.012	.025	0.99	0.77
Graduate	.035	.204	0.97	.034	.199	0.97	0.004
GPA 3.50 – 4.00	-.163	.115	1.18	-.221(p = .051)	.113	1.25	0.36
Female	-.095	.116	1.10	-.131	.116	1.14	0.22
Citizenship	-.009	.183	1.01	.323	.170	0.72	1.33
Major	.214	.136	0.81	.103	.153	0.90	0.54
Peer Composite	.123 (p = .051)	.063	1.13	**.154****	.056	1.17	0.37
Detection Composite	**-.065***	.033	0.94	.026	.032	1.03	**1.98***
Reporting Composite	.001	.029	1.00	-.054	.029	0.95	1.34
Quality	**-.051***	.023	0.95	**-.046***	.020	0.96	0.16
Costs & Benefits Composite	**.279*****	.025	1.32	**.212*****	.022	1.24	**2.01***

*p ≤ .05 **p ≤ .01 ***p ≤ .001

Among online students, the peer composite measure proved significant at the .01 level. This statistic indicates that increases in peer cheating observations increase an online student's likelihood for cheating. For each one unit increase in peer cheating observations, the average counts for overall cheating increase by 17%, when controlling for other factors. However, the impact of peer observations on traditional students is also worth noting. While the peer

composite measure failed to achieve statistical significance among traditional students, the p-value approached significance at .051. Similarly, the grade point average variable also approached significance among online students, earning a p-value of .051. This implies that peer relationships and GPA may have a behavioral influence for these students.

Lastly, the quality variable and the costs & benefits composite achieved statistical significance across both groups of students. As shown in Table 28, the quality variable achieved a p-value of less than .05 in both models. For traditional and online students, perceptions of course quality had a negative relationship with overall cheating intentions. Specifically, increases in perceived quality decreased a student's likelihood for academic dishonesty. In looking at the incidence rate ratio and z-score, the impact of quality appears quite similar across traditional students and online students. For the costs & benefits variable, a slope p-values of less than .001 were achieved within both models, suggesting that increases in perceived cheating benefits raise the likelihood for academic dishonesty. While the costs & benefits composite score appears quite influential in both models, the z-score indicates that the slopes for this variable are significantly different between traditional students and online students. In examining the slope values, it would appear that perceptions of cheating benefits are a stronger consideration among traditional students.

Academic Major & Overall Test Cheating

As shown in Table 29, split models were created based on a student's academic major. Specifically, criminal justice majors were compared against students who were not majoring in criminal justice. In Table 29, certain disparities are observed in the split models. For example, grade point average and perceptions of quality were significant among non-criminal justice majors. For grade point average, this variable was significant at the .05 level. Consistent with the previous regression models, non-criminal justice majors with a GPA of 3.50 or higher were less

likely to engage in test cheating. When controlling for other variables, non-criminal justice students with an "A" average had 23% lower average counts for overall test cheating. Additionally, course quality was highly significant among these students, reaching a significance level of .001. Among non-criminal justice students, intentions to test cheat decreased as quality increased. For each one unit increase in quality, the average count for test cheating decreased by 6%. In contrast, neither of these variables achieved significance among the criminal justice majors. Furthermore, the costs & benefits composite measure was the only variable to achieve significance among the criminal justice students.

Table 29

Split Model Negative Binomial Regression (Major & Overall Test Cheating)

	Non-Criminal Justice Major			Criminal Justice Major			
	B	SE	Exp(B)	B	SE	Exp(B)	Z
Constant	.928	.617	2.53	.697	1.98	2.01	0.11
Age	-.033	.024	0.97	-.033	.063	0.97	0.00
Graduate	-.022	.174	1.02	-.172	.531	1.19	0.27
GPA 3.50 – 4.00	**-.209***	.100	1.23	-.041	.218	1.04	0.70
Female	-.044	.101	1.05	.071	.260	0.93	0.41
Citizenship	.151	.154	0.86	-.224	.716	1.25	0.51
Course Type	.001	.099	1.00	-.087	.230	1.09	0.35
Peer Exams	.084	.113	0.92	.387	.245	0.68	1.12
Test Cheating Detection	-.013	.022	0.99	-.020	.054	0.98	0.12
Test Cheating Reporting	-.030	.020	0.97	-.055	.045	0.95	0.51
Quality	**-.067*****	.019	0.94	-.009	.046	0.99	1.17
Costs & Benefits Composite	**.249*****	.020	1.28	**.262*****	.053	1.30	0.23

*p ≤ .05 **p ≤ .01 ***p ≤ .001

When looking at the costs & benefits composite measure, this variable was significant at the .001 level within the criminal justice major model. Similarly, the costs & benefits variable also achieved a .001 significance level within the non-criminal justice major model. This indicates test cheating is more likely to occur when such actions are beneficial to a student's academic, peer, and familial goals. Moreover, in examining the incidence rate ratios and the z-score, the differences between criminal justice majors and non-criminal justice majors appear quite minimal within the context of benefits perceptions. Regardless of academic major, the effect of cheating costs & benefits appears similar.

Academic Major & Overall Plagiarism

When examining overall plagiarism intentions among non-criminal justice majors, several variables achieved statistical significance. As shown in Table 30, two variables proved significant at the .05 level among the non-majors: citizenship and quality perceptions. For citizenship, international students not majoring in criminal justice appear more likely to engage in plagiarism. When controlling for other variables, these students have 31% higher average counts for plagiarism when compared against domestic non-majors. For the quality variable, higher perceptions of course quality corresponds with lower likelihoods of plagiarism among non-criminal justice majors. Specifically, each one unit increase in quality reduces the average counts for plagiarism by 4%, when controlling for other factors.

Additionally, among the non-criminal justice major group, the variables for grade point average and female were significant at the .01 level. For grade point average, non-majors with a GPA higher than 3.50 were less likely to engage in plagiarism. When controlling for other factors, the 3.50 or better students had 33% lower average counts for plagiarism than the lower performing students. Similarly, overall plagiarism intentions were lower among female students

not majoring in criminal justice. Like the 3.50 GPA non-majors, female non-majors had 33% lower average counts for plagiarism when controlling for other variables.

Table 30

Split Model Negative Binomial Regression (Major & Overall Plagiarism)

	Non-Criminal Justice Major			Criminal Justice Major			
	B	SE	Exp(B)	B	SE	Exp(B)	Z
Constant	.370	.653	1.45	-.600	2.16	0.55	0.43
Age	-.014	.024	0.99	-.014	.071	0.99	0.00
Graduate	.181	.182	0.83	.226	.577	0.80	0.07
GPA 3.50 – 4.00	**-.287****	.107	1.33	-.463 (p = .051)	.238	1.59	0.67
Female	**-.288****	.104	1.33	-.022	.268	1.02	0.93
Citizenship	**.366***	.154	0.69	-.269	.770	1.31	0.81
Course Type	-.097	.103	1.10	**-.545***	.246	1.73	1.68
Peer Plagiarism	.168	.160	0.85	.266	.411	0.77	0.22
Plagiarism Detection	-.012	.024	0.99	-.003	.049	1.00	0.16
Plagiarism Reporting	-.021	.023	0.98	-.048	.049	0.95	0.50
Quality	**-.041***	.019	0.96	.029	.051	1.03	1.29
Costs & Benefits Composite	**.224*****	.020	1.25	**.246*****	.056	1.28	0.37

$^*p \leq .05$ $^{**}p \leq .01$ $^{***}p \leq .001$

In examining uniquely significant variables for criminal justice majors, course type was the only variable to achieve significance within the overall plagiarism model. As shown in Table 30, course type proved significant at the .05 level, suggesting that criminal justice majors were less likely to engage in plagiarism within an online course (compared to a traditional course).

Specifically, criminal justice majors in online course settings had 73% lower average counts for plagiarism, when controlling for other factors. In addition, the significance level for the GPA variable among criminal justice majors is also worth mentioning. While GPA failed to reach statistical significance within the criminal justice model, it produced a p-value of .051. As was the case for non-criminal justice majors, GPA may have an influence on a criminal justice student's likelihood for plagiarism.

Consistent with the other regression models, the costs & benefits composite measure was highly significant across both major groups. Regardless of academic major, increases in perceived cheating benefits appears to increase a student's likelihood for plagiarism. In looking at the split models in Table 30, the differences between criminal justice majors and non-majors appear minimal within the context of perceived benefits. This is evidenced by the lower z-score, which assesses the differences in slopes between non-criminal justice majors and criminal justice majors. As shown in Table 30, the z-score for the costs & benefits variable was 0.37, indicating a minor slope difference between academic major groups.

Academic Major & Overall Academic Dishonesty

In analyzing distinct cheating influences among non-criminal justice majors, student grade point average ($p \leq .01$) and perceptions of quality ($p \leq .001$) both proved significant. Among the non-majors, having a higher GPA seems reduced the likelihood for overall academic dishonesty. When controlling for other factors, non-majors with a 3.50 GPA or higher had 26% lower average counts for cheating, compared to students in the lower GPA group. For course quality, increases in perceived quality reduced the potential for cheating among non-criminal justice majors. For each one unit increase in quality perceptions, the average counts for cheating decreased by 5%, when considered alongside other variables. While both of these variables were significant among non-criminal justice majors, they failed to reach statistical significance among

criminal justice majors. Unlike the first model, the criminal justice major model had no significant variables that were unique to that group of students. Both models in Table 31 achieved statistically significant results for the composite measures of peer relationships and perceptions of cheating costs & benefits.

Table 31

Split Model Negative Binomial Regression (Major & Overall Academic Dishonesty)

	Non-Criminal Justice Major			Criminal Justice Major			
	B	SE	Exp(B)	B	SE	Exp(B)	Z
Constant	**.127***	.531	3.56	.130	1.76	1.14	0.002
Age	-.022	.020	0.98	-.020	.055	0.98	0.03
Graduate	.025	.150	0.98	-.040	.461	1.04	0.13
GPA 3.50 – 4.00	**-.227****	.088	1.26	-.173	.191	1.19	0.26
Female	-.146	.087	1.16	.025	.222	0.98	0.72
Citizenship	.186	.131	0.83	-.499	.634	1.65	1.06
Course Type	-.062	.085	1.06	-.205	.190	1.23	0.68
Peers Composite	**.116****	.045	1.12	**.221***	.108	1.25	0.90
Detection Composite	-.021	.025	0.98	.003	.053	1.00	0.41
Reporting Composite	-.023	.023	0.98	-.039	.046	0.96	0.31
Quality	**-.054*****	.016	0.95	.007	.041	1.01	1.39
Costs & Benefits Composite	**.237*****	.018	1.27	**.256*****	.047	1.29	0.38

*p ≤ .05 **p ≤ .01 ***p ≤ .001

In looking at the peer composite measure, this variable proved significant for both non-criminal justice majors and criminal justice majors. In general, increasing prior observations of

peer cheating also increased a student's likelihood for academic dishonesty. Although significant in both models, the peer composite was slightly more statistically significant among the non-criminal justice majors. While significant at the .05 level among criminal justice majors, the peer composite scored a p-value less than .01 among non-criminal justice majors. For the costs & benefits composite measure, less variation exists between the two major groups. This is evidenced by the low z-score, indicating minor differences in slopes between academic majors. In general, perceptions of costs & benefits were highly influential among both non-criminal justice and criminal justice majors, reaching significance at the 001 level. This finding is fairly consistent with the other regression models, showing how cheating benefits are strongly considered among students in their intentions to commit academic dishonesty.

Anti-Cheating Software & Online Courses

In this study, the use of anti-cheating software also was measured. For students completing the online course survey, three questions pertaining to instructor use of anti-cheating software were added. Specifically, online course participants reported the level of webcam, Turnitin®, and Respondus use within a fully online class. These variables were coded as scale measures, where "0 = 0% prior use" and "10 = 100% prior use" by online instructors. To further assess the influence of these variables, three negative binomial regression models were created using the composite cheating variables for test cheating, plagiarism, and overall cheating. In general, each of these software programs reached statistical significance in predicting at least one of the dependent variables.

Overall Test Cheating Among Online Students

For Table 32, overall test cheating behaviors among online students were analyzed. In addition to the previously included variables, this negative binomial regression model included three variables pertaining to software use. Among these software variables, webcam and

Turnitin® were both significant at the .05 level. For webcam, this finding indicates that greater prior use of webcams during an assessment influences a student's likelihood for test cheating engagement. For each one unit increase in prior webcam use, the average counts for test cheating decreased by 5% when controlling for other factors. Interestingly, prior use of Turnitin® also influenced the likelihood for test cheating, even though Turnitin® is generally associated with plagiarism detection. When controlling for other variables, each one unit increase in prior Turnitin® use increased the average counts for test cheating by 4%.

In addition to these software variables, the peer exam variable ($p \leq .05$) and costs & benefits composite measure ($p \leq .001$) also were significant in predicting test cheating among online students. More precisely, the likelihood for test cheating appears higher among online students who have previously observed peer exam cheating and who have greater perceptions of cheating benefits. These findings are somewhat different to those presented within Table 26. Table 26 used split modeling to examine overall test cheating behaviors based on course type. For the online student model, only the quality variable and the costs & benefits composite achieved statistically significant results. While the costs & benefits composite remained relatively unchanged, adding the current software variables to the regression model caused the quality variable to lose significance and the peer variable to gain significance. This may imply that software variables mediate the relationship between quality perceptions and overall test cheating intentions.

Table 32

Negative Binomial Regression (Online Student Test Cheating & Software)

	B	SE	Exp(B)
Constant	.596	.634	1.81
Age	-.019	.029	0.98
Graduate	.037	.224	1.04
GPA 3.50 – 4.00	-.186	.128	0.83
Female	-.021	.131	0.98
Citizenship	.291	.202	1.34
Major	.166	.174	1.18
Peer Exams	**.290***	.138	1.34
Test Cheating Detection	.006	.029	1.01
Test Cheating Reporting	-.022	.026	0.98
Quality	-.040	.024	0.96
Costs & Benefits Composite	**.230*****	.025	1.26
Webcam	**-.055***	.024	0.95
Turnitin	**-.040***	.020	0.96
Respondus	.047	.025	1.05

*$p \leq .05$ **$p \leq .01$ ***$p \leq .001$

Overall Plagiarism among Online Students

Table 33 analyzes overall intentions to plagiarize among online students. Similar to the previous negative binomial regression model, the three anti-cheating software variables were added to this analysis. Among these software variables, the Turnitin® variable proved significant at the .05 level. This indicates that prior use of Turnitin® reduces the likelihood for future

plagiarism incidents among online students. When controlling for other factors, each one unit increase in prior Turnitin® use decreases the average counts for plagiarism by 5%. In general, this is a logical finding, as Turnitin® is designed to detect incidents of plagiarism within course assessments. Additionally, four other variables achieved significance within this regression model.

Table 33

Negative Binomial Regression (Online Student Plagiarism & Software)

	B	SE	Exp(B)
Constant	.169	.685	1.18
Age	-.014	.031	0.99
Graduate	.207	.248	1.23
GPA 3.50 – 4.00	**-.310***	.138	0.73
Female	-.239	.140	0.79
Citizenship	**.511***	.210	1.67
Major	-.054	.205	0.95
Peer Plagiarism	**.521****	.196	1.68
Plagiarism Detection	.016	.030	1.68
Plagiarism Reporting	-.030	.029	0.97
Quality	-.016	.026	0.98
Costs & Benefits Composite	**.176*****	.025	1.19
Webcam	-.007	.026	0.98
Turnitin	**-.050***	.022	0.95
Respondus	.032	.026	1.03

$*p \leq .05$ $**p \leq .01$ $***p \leq .001$

Among the demographic variables, grade point average and citizenship both achieved p-values less than .05. This suggests that intentions to plagiarize are higher among students with lower than 3.50 grade point averages, as well as international students. Among the perceptual variables, prior observations of peer plagiarism ($p \leq .01$) and the costs & benefits composite ($p \leq .001$) both achieved significance. More precisely, the average counts for plagiarism intentions were higher among students who previously witnessed peer plagiarism and for students who perceive greater cheating benefits. Overall, these findings were fairly consistent with the split model in Table 27. As previously discussed, Table 27 highlights the differences in overall plagiarism among both traditional and online students. In the online setting model of Table 27, all four of these variables achieved statistically significant results. Even with the addition of software variables in this current model, statistical significance was retained for GPA, citizenship, peer plagiarism, and overall costs & benefits.

Overall Academic Dishonesty Among Online Students

In Table 34, overall cheating intentions among online students were analyzed through use of negative binomial regression. In this model, two software variables achieved significance at the .05 level: Turnitin® and Respondus. For Turnitin®, the results suggest that greater prior use of Turnitin® within an online course reduces the likelihood for future cheating behaviors. With each one unit increase in prior Turnitin® use, the average counts for overall cheating decreased by 4%, when controlling for other factors.

Table 34

Negative Binomial Regression (Online Student Academic Dishonesty & Software)

	B	SE	Exp(B)
Constant	**1.14***	.557	3.13
Age	-.012	.025	0.99
Graduate	.091	.200	1.10
GPA 3.50 – 4.00	**-.239***	.114	0.79
Female	-.122	.116	0.89
Citizenship	**.355***	.177	1.43
Major	.107	.158	1.11
Peer Composite	**.180****	.057	1.20
Detection Composite	.022	.033	1.02
Reporting Composite	-.040	.029	0.96
Quality	-.031	.022	0.97
Costs & Benefits Composite	**.216*****	.022	1.24
Webcam	-.041	.022	0.96
Turnitin	**-.044***	.018	0.96
Respondus	**.045***	.022	1.05

*$p \leq .05$ **$p \leq .01$ ***$p \leq .001$

Interestingly, the Respondus variable produced contrary findings. Based on the statistics in Table 34, greater prior use of Respondus increased the likelihood for academic dishonesty among online students. When controlling for other variables, each one unit increase in previous Respondus use resulted in a 5% increase in average counts of total cheating among online

students. In conducting all regression analyses, tests for multicollinearity and serial autocorrelation were completed, as serious issues concerning multicollinearity or autocorrelation could explain these unexpected findings for Respondus. However, these tests yielded satisfactory tolerance statistics, variance inflation factors, and the Durbin-Watson statistics, suggesting that these regression assumptions were met within the models. As such, the results of this model would imply that Respondus is an ineffective tool in reducing cheating among online students, while controlling for other variables. In fact, these findings actually suggest that use of Respondus may lead to greater academic dishonesty among online students.

When comparing the findings from this model to those presented in Table 28, certain differences are observed. As previously mentioned, Table 28 compared overall cheating among traditional students and online students. In the online student model of Table 28, grade point average and citizenship failed to achieve statistically significant p-values. However, adding the three software factors to the regression model has caused a change in significance for these demographic variables. As shown in the current model, both GPA and the citizenship are significant at the .05 level, suggesting that the likelihood of overall cheating is lower among "A" grade students and domestic students.

When looking at the significance levels among the perceptual measures, the addition of software variables led to some minor adjustments. While the peer composite and the costs & benefits composite variables retained their respective p-values, the p-value for course quality changed in this current model. The addition of these three software variables caused the quality variable to lose significance. While the quality variable was significant at the .01 level in Table 28, perceptions of course quality were no longer significant among online students when prior software use was considered. As such, these software variables may mediate the relationship between perceptions of course quality and overall cheating intentions.

Summary

The purpose of this chapter was to present the results of this study derived from quantitative analysis. As previously discussed, this study collected 1,084 student responses from one New England university. Using this data, a series of descriptive, bivariate, and multivariate analyses were conducted in order to identify influences on student academic dishonesty. Upon examination of these statistical models, promising findings were derived concerning academic dishonesty.

As previously stated, one of the primary functions for running descriptive statistics was to identify issues such as overrepresented populations. Based on the frequency distributions for the demographic variables, this study attracted a diverse group of students across the campus. In general, students of different academic schools, genders, ages, and citizenship status participated within this research. Despite “A” grade students being overrepresented in this research, the sample seems to adequately represent of campus community. Additionally, the frequency distributions for each variable provide preliminary insight concerning the variables. In comparing frequency statistics among traditional and online students, the differences seemed notable. More precisely, the behaviors and perceptions of online students seemed quite different than traditional students. To more fully examine these differences, bivariate analyses were conducted.

Building off of the descriptive statistics, a series of bivariate models were generated to further explore influences on academic dishonesty. More precisely, this study used chi-square modeling, Pearson correlation coefficients, and analysis of variance (ANOVA) to fully investigate these relationships between variables. In general, these statistical models generated insightful research findings as nearly all of the variables had statistically significant influences on some form of academic dishonesty. The bivariate results for course type, academic major, and

the rational choice variables were especially noteworthy. For course type, the bivariate results indicated that online students displayed distinct behaviors within certain cheating contexts. For academic major, criminal justice majors seemed to display equivalent cheating intentions to other students. Lastly, the rational choice variables measuring peer influences, cheating detection, formal reporting, and perceptions of cheating costs & benefits all produced significant results, providing quantitative support for this study's theoretical framework and hypotheses. Unfortunately, many of these statistically significant variables lost significance within the multivariate models.

The multivariate analyses presented within this study provided the greatest insight concerning academic dishonesty intentions among college students. Unlike the bivariate models that examined the influence of single variables on cheating intentions, these multivariate models considered interaction effects between multiple independent variables. As such, significant variables in both the bivariate and multivariate models would appear the most influential on college student cheating. In this research, several variables did achieve statistically significant results in both forms of quantitative analysis. Specifically, the results for course type and perceptions of costs & benefits were especially pronounced. Through these multivariate models, further context into academic dishonesty among online students was provided. Based on the results of the logistic regression models and the negative binomial regression models, online students seem to have distinct considerations and behaviors within cheating intentions. These results can have profound implications on institutional policy, as discussed in the conclusions chapter. The findings for perceptions of cheating costs & benefits generated the most noteworthy results within this research. The variables concerning perceived cheating costs & benefits achieved statistically significant results within every model in this study. Moreover, these

benefits variables achieved p-values less than .001 in each of these analyses. This would indicate that student intentions to cheat are highly influenced by anticipated benefits.

Overall, the data employed in this study produced encouraging results for college student cheating research. As shown in this chapter, every independent variable achieved a statistically significant result in at least one model. This would imply that the independent variables chosen for this study were appropriate within this context of academic dishonesty. Furthermore, the significant findings for the rational choice variables provide compelling evidence that rational choice theory was an appropriate theoretical framework within this research project. Finally, the results from this study can be used to guide institutional policy and initiatives to reduce college student cheating.

CHAPTER SIX

Discussion & Conclusions

When initially conceived, this study sought to consider how behaviors in college student cheating have changed since the start of the Covid-19 pandemic. In response to public health restrictions, higher education shifted heavily towards an online or remote learning model for course delivery. While this change was necessitated, its impact on academic misconduct remained relatively unknown to institutions. Since online learning likely will serve a prominent role within higher education for the foreseeable future, research into current cheating behaviors was warranted. As such, this study collected original data and examined the influence of different variables on the likelihood of college academic dishonesty. To fully explore this issue, rational choice theory was used as the theoretical framework for the research.

In this study, several independent variables were created that directly reflect principles of rational choice theory. These included factors related to cheating detection, formal reporting for cheating, peer influences, and the costs and benefits of cheating. For this study, these variables guided the development of the research hypotheses. Each of these hypotheses presented conditions or characteristics where higher rates of academic dishonesty were expected. These hypotheses then were tested through the use of various univariate, bivariate, and multivariate statistics. This final chapter highlights the key findings of the quantitative analysis, corresponding policy implications, research limitations, and directions for future research.

Key Findings

Cheating in Online Courses

A central inquiry within this research was to identify distinctions in cheating behaviors for traditional and online students. In response to the Covid-19 pandemic, higher education relied heavily on remote learning models for students. As a result, a much larger proportion of college

students were enrolled in online courses for the 2020 – 2021 academic year. Furthermore, these trends in remote learning likely will continue for the foreseeable future. As such, the impact of these enrollment changes on student academic dishonesty were considered within this research. This study initially hypothesized that online students would engage in higher rates of academic dishonesty than traditional students. With the physical disconnection of students from instructors, it was predicted that academic misconduct would be easier to pursue. To investigate this hypothesis, a series of bivariate tests and multivariate models were generated. While certain disparities appeared among online students, these differences were not as pronounced as initially suspected. Moreover, this hypothesis was only partially supported within statistical testing.

Higher Intentions

In the bivariate tests, the impact of course type on nine cheating behaviors initially were analyzed. In reviewing the chi-square statistics (Table 10), course type was significantly associated with three test cheating variables: test copying, test collusion, and test cribnotes. For each of these variables, online students expressed a greater likelihood for cheating engagement than traditional students. When referencing the respective logistic regression models for these three dependent variables, the influence of course type on test cheating was further revealed. For test copying (Table 14) and test collusion (Table 15), course type was statistically significant when considered alongside demographic variables. However, upon introduction of perceptual variables, course type lost significance within these models. This suggests that when perceptual factors are considered, the influence of course type on these test cheating variables was not as important or was mediated by the perceptual variables.

In contrast, course type remained significant in both logistic regression models for test cheating cribnotes (Table 17). This indicates that potential use of cribnotes was higher among online students, even when perceptual factors were considered. These differences were first

revealed within the chi-square models when test cheating cribnotes achieved the strongest p-value ($p \leq .001$). The results of the logistic regression model further highlighted distinctions between the traditional and online class settings in terms of cribnote use. In general, these findings are fairly consistent with prior research findings. In previous studies, researchers argued that remote learning environments may generate greater engagement in test cheating due to the lack of instructor oversight (Harmon et al., 2010; Stuber-McEwen et al., 2009; Sun & Chen, 2016). At least in terms of cribnote use, this appears to be the case.

The findings for overall test cheating engagement are also worth noting. In looking at overall test cheating behaviors, as shown in the negative binomial regression model (Table 26), the differences between traditional students and online students appear minimal. While online students may be more likely to engage in certain forms of test cheating, such as cribnote use, overall intentions for test cheating appear quite similar to traditional students. Additionally, while certain cheating behaviors appeared higher among online students, other models found lower intentions for cheating among these students.

Lower Intentions

The logistic regression models for test cheating advance (Table 16), plagiarism padding (Table 21), and plagiarism copying (Table 22) generated findings suggesting that online students have lower likelihoods for these types of cheating engagement. For all three of these models, differences between traditional and online students were statistically significant. The findings for test cheating advance seem logical. The test cheating advance variable measured a student's likelihood for receiving exam questions or answers ahead of an exam. In online settings, students typically are more disconnected from classmates than within traditional classroom settings (Sun & Chen, 2016). As such, receiving questions or answers from a classmate may prove more difficult for online students. The results from the two plagiarism models might be harder to

explain. Based on the logistic regression models, online students had lower likelihoods for creating false citations in a bibliography and for copying sentences into a paper without citing. For these findings, however, instructor use of Turnitin® is perhaps influencing these likelihoods. As shown in the negative binomial regression models (Tables 32 to 34), prior use of Turnitin® appears to decrease an online student's likelihood for academic dishonesty. Within remote courses, instructors may utilize this software more frequently, leading to lower plagiarism intentions among online students.

In reviewing all the statistical models, the lack of consistency for online student cheating engagement was unexpected. When developing this research study, it was predicted that online students would report higher intentions to cheat across all academic dishonesty variables. However, the results of the data analysis are mixed. For test cheating, engagement in this form of academic dishonesty (particularly cribnote use) does appear higher among online students, although other perceptual variables are important to consider. Interestingly, when analyzing certain plagiarism behaviors, the opposite appears true: online students appear less likely to commit plagiarism than traditional students. Overall, these findings suggest that online students are more susceptible to test cheating while traditional students are more likely to plagiarize. As such, efforts to reduce academic dishonesty may require targeted initiatives for both traditional students and online students. Based on the regression model results, webcams may prove more effective in reducing online test cheating, while Turnitin® use could reduce plagiarism among both online and traditional students.

Cheating Among Criminal Justice Majors

When looking at previous studies of academic dishonesty among criminal justice majors, the literature is quite limited. While several studies have examined behavioral distinctions among criminal justice majors (Coston & Jenks, 1998; Eskridge & Ames, 1993; Lambert & Hogan,

2004; Tibbetts, 1998), these studies are dated. As such, cheating behaviors among current criminal justice majors were examined extensively through quantitative analysis. This study hypothesized that criminal justice majors would engage in lower levels of academic dishonesty when compared against non-criminal justice majors. This hypothesis was derived from the behavioral expectations of criminal justice graduates. In general, students in a criminal justice program are often preparing for careers in public service and law enforcement. During classes, these students are often exposed to courses about ethical behavior and decision-making (Byers & Powers, 1997; Coston & Jenks, 1998; Tibbetts, 1998). For this reason, it was expected that these students would display higher levels of integrity within their behaviors (Coston & Jenks, 1998; Tibbetts, 1998). In reviewing the statistical models, this hypothesis was not substantiated.

In most of the statistical models, there was a relative equivalence in academic dishonesty across criminal justice and non-criminal justice majors. In general, this is consistent with previous studies that found no behavioral differences among criminal justice and non-criminal justice majors (Eskridge & Ames, 1993; Lambert & Hogan, 2004). Unfortunately, this study also identified certain areas where criminal justice majors had greater intentions for cheating. For example, the logistic regression models for test copying (Table 14) and test cribnotes (Table 17) revealed that criminal justice majors were more willing to engage in these cheating behaviors (the differences were significant at the .05 level). These findings, alongside the non-significant findings in other models, would imply that criminal justice majors are not displaying higher levels of morality (or lower levels of academic dishonesty) as initially expected. In certain circumstances, these students may be displaying lower levels of ethical decision-making than other academic majors.

Cheating Detection

This study hypothesized that increases in cheating detection perceptions would correspond with lower rates of academic dishonesty. In several previous studies, researchers argued that academic dishonesty is more likely to occur when cheating detection is low (Freiburger et al., 2017; Nagin & Pogarsky, 2003; Walters & Morgan, 2019). As such, this study employed a similar mindset, hypothesizing that perceptions of instructor detection would greatly influence a student's intention to cheat. Based on the data analysis, this hypothesis was not supported.

For the Pearson correlation coefficients, the detection variables appeared to have statistically significant relationships with overall test cheating, overall plagiarism, and overall academic dishonesty. However, in the multivariate models, the detection variable proved insignificant. In general, findings from a multivariate analysis often provide stronger evidence regarding the impact of an independent variable on a dependent variable. Significance in the bivariate statistics implied that perceptions of detection had a significant influence on various forms of academic dishonesty, but loss of significance in the multivariate models indicated that the detection variable was not as important to student decision-making, when considered alongside other relevant factors. The lone exception was in the negative binomial regression split model for overall cheating. In this split model, the detection variable was statistically significant ($p \leq .05$) among traditional students, while insignificant among online students. This may suggest that students consider cheating detection to be a greater threat within traditional courses than online courses. However, the lack of significance in nearly all of the multivariate models would more strongly imply that the likelihood of detection does not influence student intentions for academic misconduct.

Formal Reporting for Cheating

Similar to the detection variable, the perceived likelihood for formal reporting does not appear to influence student intentions to cheat. As previously mentioned, formal reporting for academic dishonesty is quite low among universities. While self-reported rates of student cheating are often high, only a small percentage of students are formally disciplined by a university for academic misconduct (Freiburger et al., 2017; Happel & Jennings, 2008; McCabe et al., 2012; Staats et al., 2009). As such, this study hypothesized that academic dishonesty would be higher when the risk for formal reporting is lower.

Based on the descriptive statistics for formal reporting, students seem to acknowledge the risk for formal reporting for cheating. Examination of the Pearson correlation coefficients suggest that increases in formal reporting decrease overall academic dishonesty rates. However, these significant findings were lost within most of the multivariate models within this study. This implies that that formal reporting does not influence a student's intentions to cheat, when other factors are considered. The two exceptions were in the logistic regression models for test copying (Table 14) and test cribnotes (Table 17). In both of these logistic regression models, the formal reporting variable did prove significant at the .05 level. More precisely, increases in perceptions of formal reporting decreased the likelihood for test copying and cribnotes use during an exam. Unfortunately, the formal reporting variable yielded insignificant findings in the remaining logistic regression models and in the negative binomial regressions. While students may consider the risk of formal reporting more seriously in choosing certain test cheating behaviors, the overall impact of this variable appears limited.

Peer Relationships

Criminal Justice Majors

In the context of academic dishonesty, previous research studies have posited that peer relationships appear more influential to criminal justice students than other majors (Lambert & Hogan, 2004; Tibbetts, 1998). As such, this study hypothesized that similar results would be observed during quantitative analysis. In examining the split academic major models for overall test cheating, overall plagiarism, and overall academic dishonesty, no significant differences in peer influences were observed. More precisely, the impact of peer relationships appears quite equitable across all college students. This is evidenced by the insignificant z-scores for peer variables in the negative binomial regression split models. Had notable differences occurred between these two academic major groups, the z-scores would have reached statistical significant. Furthermore, the peer variable only achieved statistically significant p-values within the overall academic dishonesty model. While peer observations do seem to influence a criminal justice student's overall likelihood for cheating, a similar effect is also observed among non-criminal justice majors.

Online Students

In examining the impact of peer relationships on online students, interesting findings were derived from the statistical models. Given the independent nature of online courses, this study hypothesized that peer relationships would have a reduced effect on student behaviors within online courses. Remote learners historically are often disconnected from their fellow classmates, making peer interactions more limited (Sun & Chen, 2016). As such, peer influences should have a lesser impact on online students than traditional students. The statistical models within this study suggested the opposite, however.

In the negative binomial regression split models for overall plagiarism (Table 27) and overall academic dishonesty (Table 28), peer relationships proved statistically significant among online students, while insignificant among the traditional students. Moreover, the z-score within the overall plagiarism model suggested that the influence of peer observations of plagiarism was significantly different between traditional students and online students. For online students, observing an online peer engage in plagiarism increased average counts for overall plagiarism intentions. This finding implies that modern online students may be more connected to, and influenced by, their fellow peers than in previous semesters. Moreover, this finding suggests online learning dynamics have changed during this current pandemic, and colleges should acknowledge peer influences within remote courses.

Female Students

This study initially hypothesized that no major cheating disparities would exist between students of different genders. This position generally was derived from the inconclusiveness of previous research concerning gender distinctions in academic dishonesty. While some studies have found less cheating among female students (Bowers, 1964; McCabe & Trevino, 1997; Whitley et al., 1999), more recent research has argued that these gender distinctions are becoming less apparent (McCabe et al, 2012; Whitley, 2001). With the higher enrollment of females within higher education, it was suspected that cheating behaviors would be quite similar across different genders. In analyzing the collected data for this study, this hypothesis was partially substantiated.

For the models using test cheating as the dependent variable, no significant differences emerged among female and non-female students. When analyzing the four dichotomous measures for test cheating, the female variable failed to achieve statistically significant results in the chi-square statistics and the logistic regression models. Furthermore, the female variable also

proved insignificant in the negative binomial regressions for overall test cheating and overall academic dishonesty. As such, it appears that females and non-females behave relatively similarly when analyzing exam cheating and overall academic dishonesty.

For plagiarism behaviors, however, notable gender differences emerged within the quantitative models. In looking at the chi-square statistics and the logistic regression models for these variables, statistically significant differences were observed for plagiarism collusion, plagiarism material, and plagiarism copying. Female students expressed lower likelihoods of submitting papers completed by someone else, plagiarizing public material, and copying sentences without citing. This finding was further validated within the negative binomial regression model for overall plagiarism behaviors (Table 24). In this negative binomial model, female students had lower average counts for plagiarism than non-females. Overall, these findings suggest that gender differences in cheating are situated in the context of certain plagiarism behaviors.

Grade Point Average

Within this study, the GPA variable proved quite significant within a number of the multivariate models. However, the precise relationship between GPA and academic dishonesty is difficult to surmise from this dataset. In this study, 64% of the participants identified GPA's within the "A" range, while an additional 25.7% of students claimed "B" averages. As such, nearly 90% of the participants were high performing academic students. To handle this issue within multivariate analysis, the GPA variable was recoded into a dichotomous measure, where students were separated into a "3.50 or higher" GPA group and a "lower than 3.50" GPA group. As such, the analyses being performed on GPA essentially compared behaviors of "A" students and "lower than an A" students at the university.

In nearly all the full logistic regression models, test cheating collusion and test cheating advance being the exceptions, the recoded GPA variable proved statistically significant. More precisely, seven forms of academic dishonesty appear less likely to occur among "A" grade students. Furthermore, significant findings were also derived within the negative binomial regression models for overall plagiarism (Table 24) and overall academic dishonesty (Table 25). In general, these finding are consistent with previous research, showing that higher achieving students engage in academic dishonesty at lower rates (McCabe et al., 2012; Olafson et al., 2013). While this study determined that "A" students show lower likelihoods for cheating engagement, it is less clear as to how these cheating behaviors vary across more specific GPA groups.

International Students

This study initially hypothesized that international students would show greater likelihoods for academic dishonesty. This hypothesis was derived from prior research concerning international students and the difficulties they face with course assessments (Amsberry, 2010; Bista, 2011). In reviewing the statistical models, this hypothesis appears to be supported by the data. In most of the multivariate models, differences between international and domestic students were statistically significant. In reviewing the full logistic regression models, international students had higher likelihoods for various forms of test cheating (copy, collusion, advance) and plagiarism (collusion, material, copy).

The findings from the negative binomial regression analyses further supported these results, yielding statistically significant differences for international students. The negative binomial models suggest that plagiarism risk is especially high among international students. This is a logical finding, as cultural differences among international students can make written assignments more difficult to complete (Amsberry, 2010; Bista, 2011; Hayes & Introna, 2005;

Simpson, 2016). As a result, international students may unintentionally engage in plagiarism behaviors or make plagiarism decisions differently from domestic students. Overall, these findings imply that international students are more likely to engage certain forms of cheating than domestic students.

Younger Students

This study initially hypothesized that younger students would express greater intentions to cheat. While this hypothesis was partially supported in statistical analysis, the findings were less than compelling. With a few exceptions, the age variable proved insignificant in the statistical models. While the Pearson correlation coefficients yielded significant findings for the age variable, these results were not sustained in most multivariate analyses. As shown in the initial logistic regression models, age was statistically significant for five cheating behaviors, when compared against other demographic variables. However, when perceptual variables were added, age lost significance in most of the models. The logistic regression for test cheating advance was the only behavior where age retained significance after the perceptual factors were included. The results of the negative binomial regression models displayed even lower evidence of an age influence on student cheating. In these negative binomial models, age failed to achieve any statistically significant findings. While student age may influence cheating likelihoods for certain behaviors, the impact appears quite minimal when other factors are considered.

Quality

As an additional line of inquiry, data concerning student perceptions of course quality were collected. Specifically, this study sought to examine whether satisfaction with course quality influenced a student's likelihood for academic dishonesty. During quantitative analysis, the quality variable achieved statistically significant results across multiple models. Specifically, the quality variable achieved significant p-values in several of the logistic regression models and

the negative binomial regressions. The data indicate that the likelihoods for certain cheating behaviors are reduced when perceptions of course quality are increased. The influence of quality was especially pronounced within the test cheating statistical models. As such, students dissatisfied with a course appear to have greater susceptibility for test cheating engagement.

Costs & Benefits

As previously discussed, rational choice theory served as the theoretical framework for this research study. From the rational choice perspective, consideration of costs and benefits in human behavior is a hallmark principle. As such, three variables concerning perceived costs & benefits were added to the student surveys. These items asked students to consider how costly or beneficial cheating was to their academic goals, peer relationships, and familial relationships. These three variables were then used to create an overall benefits composite measure, where the average score of these three variables was calculated. This composite score reflected overall perceptions of cheating costs & benefits among the participants. As previously stated, this survey question could have been improved by focusing on perceptions of costs and having each scale increment represent a percentage of perceived costliness. Nonetheless, in every statistical model within this study, the costs & benefits composite variable achieved statistically significant results at the .001 level. This indicates that consideration of cheating costs & benefits consistently influences student cheating behaviors.

Anti-Cheating Software

Among students assigned to the online course survey, three additional questions concerning anti-cheating software were added. For these questions, students reported use of webcams, Turnitin®, and Respondus Lockdown Browser within prior online courses. In analyzing the results of the negative binomial regression models, each piece of software achieved statistically significant results in at least one model. For the model analyzing overall test cheating

behaviors, previous use of webcams had a negative relationship with the average count for test cheating intentions. This suggests that prior use of webcams during online exams decreases an online student's likelihood for future test cheating.

For Turnitin®, statistically significant results were observed in all three models analyzing overall test cheating, overall plagiarism, and overall academic dishonesty. In all three of these models, Turnitin® generated a significant negative effect, indicating that greater prior use of Turnitin® decreases a student's likelihood for various forms of academic dishonesty. While Turnitin® is as a plagiarism detection software, it appears to be an effective tool in reducing multiple forms of academic misconduct. Unfortunately, the impact of Respondus Lockdown Browser on overall academic dishonesty did not derive such promising results.

In the overall academic dishonesty model, the Respondus variable achieved statistically significant results. However, the positive effect indicates that prior use of Respondus Lockdown Browser seems to increase a student's likelihood for future academic dishonesty. This was an unexpected finding, as Respondus Lockdown Browser is designed to reduce cheating incidents. The findings from this study suggest that not only is Respondus ineffective in reducing cheating, use of this software may actually contribute to greater academic dishonesty. Several logical explanations for this finding can be presumed. Respondus Lockdown Browser prevents students from accessing online resources during an examination. Specifically, this software locks students into a specific course assessment on their web browser. Unfortunately, students still are able to access hardcopy references when working on these assignments. In anticipation of Lockdown Browser use, online students potentially can prepare physical notes or use other hardcopy resources for a remote assessment. Relatedly, Respondus does not prevent student web access on alternative devices such as tablets and cell phones. As such, students may employ certain strategies to overcome challenges presented by Respondus. For certain students, the prospect of

outsmarting a professor's Respondus mandate may actually encourage engagement in academic dishonesty.

Policy Implications

Overall, this study produced a variety of results concerning factors that influence contemporary academic dishonesty. In analyzing and reviewing the data, certain variables proved significant in elevating the likelihood of cheating among college students, while other factors were not significant. As such, institutional policies should address these influences and seek to reduce cheating behaviors among students. Specifically, policy implications should center on addressing cheating as it relates to online versus traditional courses, criminal justice majors, international students, sanctioning, course quality, and software use within online and traditional classes.

First, the results of this study should alleviate concerns for heightened student cheating within online courses. While this study initially hypothesized that online courses would invite more academic dishonesty among students, this was not supported to a great extent through the quantitative evidence. Although certain forms of test cheating may be more common in an online course, most of the statistical models found equivalent behaviors between the traditional and online settings. In certain areas, online students actually expressed lower intentions to cheat than traditional students. As cheating behaviors are fairly comparable among in-person and online learners, colleges should feel comfortable integrating more online courses within their curriculums. For institutions that are concerned about heightened test cheating within online courses, targeted initiatives can be enacted. Specifically, prior researchers have argued that online instructors should focus less on traditional exams and emphasize more open-ended assessments (Harmon et al., 2010; Watson & Sottile, 2010). This change should diminish the issue of higher test cheating intentions among online students.

Second, this research revealed some concerning findings for criminal justice departments. While it is often expected that criminal justice majors will display higher levels of integrity and ethics, the findings from this research do not support this argument. In most of the statistical models, criminal justice students expressed similar cheating intentions to other student majors. In several cases, criminal justice majors actually expressed greater intentions to cheat. For college students, cheating behaviors during college can reverberate beyond a person's academic tenure (Sims, 1993). Specifically, students who behave immorally often mirror these behaviors during their professional careers. As such, substantial cheating among criminal justice majors may pose issues to the overall field of criminal justice. Based on these findings, curriculum modifications within criminal justice courses appear warranted. Incorporating more ethics training into criminal justice courses could educate these students about the importance of moral decision-making. In response, criminal justice students may adopt more honest behaviors when completing academic assignments. Furthermore, this may set a foundation for students to behave more ethically as criminal justice professionals.

Third, this study found notable distinctions in cheating intentions among international students. Specifically, international students appear more likely to cheat than domestic students. As previous literature has indicated, cultural differences and language barriers can make academic coursework more challenging for international students (Amsberry, 2010; Beasley, 2016; Bista, 2011; Hayes & Introna, 2005). In many instances, engagement in academic dishonesty appears unintentional among these students (Beasley, 2016; Bista, 2011; Hayes & Introna, 2005). For colleges with a larger international student population, academic support services should provide adequate services to these foreign cohorts. Unfortunately, a common challenge for colleges is underutilization of support services by international students (Eisenberg et al., 2007; Jackson et al., 2013). However, this may stem from a lack of awareness about the

availability of these services. By building awareness for these programs and encouraging (or requiring) greater participation, international students can pursue assistance and learn appropriate behaviors for academic coursework.

Fourth, the benefits composite measure was consistently significant across all the statistical models within this study. In general, intentions to cheat were lower when such actions were perceived to negatively impact academic success, peer relationships, and familial relationships. In terms of policy development, institutions should consider ways to integrate these findings into student life, professional development activities, and sanctioning. For example, colleges could refocus resources on the cultivation of student relationships with peers and family members while also promoting personal academic success. In response, students may be less likely to commit academic misconduct, as university sanctions may prove costly to these personal achievements. Typically, sanctions for cheating may involve an academic punishment issued by an institution. When it comes to cheating punishments, these research findings would imply that sanctions that potentially compromise a student's peer and familial relationships can prove effective at reducing cheating intentions. For example, punishments such as removal from a residence hall or parental notification for cheating can negatively influence peer and family relationships, possibly reducing a student's likelihood for choosing academic dishonesty.

Fifth, colleges should emphasize the quality of instruction they are delivering to students. As demonstrated within this study, perceptions of quality had a fairly consistent impact on student likelihoods for academic dishonesty. More precisely, higher perceptions of course quality reduced student cheating intentions. These findings have clear implications for institutional policy. Specifically, delivering high quality education to students should be a key consideration within the mission, operations, and strategic planning of an institution. During hiring, administrators should place strong emphasis on the teaching effectiveness of instructors. Hiring

talented professors likely would translate into higher student perceptions of course quality and added reputability for an institution. Furthermore, constructive use of student course evaluations and corresponding professional development should be encouraged. In course evaluations, students often present an instructor with recommendations for course improvement. In general, instructors should be receptive to this student feedback and should be encouraged to integrate these ideas into future courses. In doing so, course quality can improve, and students may display lower likelihoods for academic dishonesty.

Lastly, institutions should reconsider the types of anti-cheating software they utilize within online courses. More precisely, the findings for Turnitin® and the Respondus Lockdown Browser have the greatest implications for collegiate policy. For Turnitin®, this tool proved quite effective in reducing multiple forms of academic dishonesty. While Turnitin® is designed as an anti-plagiarism tool, the findings indicate that prior use of this software can reduce intentions for test cheating, plagiarism, and overall academic dishonesty. Alternatively, the Respondus Lockdown Browser yielded less desirable findings within this research, suggesting a general ineffectiveness in reducing student cheating. In analyzing the impact of Respondus, prior use of this tool may even promote overall cheating intentions among online students. As previously mentioned, Respondus only prevents concurrent online computer resources from being accessed. For students who are intent on cheating, workarounds to the Respondus Lockdown Browser can be utilized, such as referencing hardcopy notes or accessing online resources on a secondary device. As such, online instructors should carefully select which software they choose to integrate within their courses.

Research Limitations

In reviewing the methodology and findings from this study, certain limitations do exist. Specifically, concerns over generalizability are especially relevant, as the sampling strategy employed within this study presents certain issues. First, only one institution was selected for the data collection process. As such, the results cannot adequately represent the entire college student population. Had multiple institutions been included in the data collection process, more generalizable findings could have been achieved. Additionally, use of an online survey was necessary, but may have weakened certain aspects of the research.

Due to university restrictions resulting from the Covid-19 pandemic, an online survey distribution was the most feasible methodology for this study. With this online survey, the student body was emailed an invitation to participate in the research project. Students who agreed to the terms were directed to a survey link where they responded to a variety of prompts. While current circumstances made this the most feasible approach, online surveys do pose challenges within research projects. The most commonly cited challenge with online surveys is the typically lower response rate (Dillman, 2014). In general, higher response rates are desired, especially when a sampled institution is smaller in size. In this study, a response rate of approximately 16% was achieved. Although this is a relatively high figure for an online survey, in-person distribution of surveys in classes likely would have yielded a higher response rate.

An added challenge with online surveys is the attraction of likeminded participants within a sample. In looking at this study, higher achieving students (those with a 3.00 GPA or higher) comprised nearly 90% of the sample. This would suggest that participation in this study was more appealing to this group of students. In general, overrepresentation by certain groups can present challenges within statistical analysis. For this study, this proved particularly true when analyzing the influence of GPA on student likelihoods for cheating. With an underrepresentation

of lower achieving students, the relationship between GPA and academic dishonesty could not be fully explored. As a result, this further weakened the generalizability of this research study. Overall, the limitations present within this study should help guide future studies into academic dishonesty.

Directions for Future Research

In conducting future studies into academic dishonesty, researchers should consider the limitations and notable findings from this research. In referencing this study's limitations, certain methodological strategies should be considered in subsequent studies to strengthen generalizability. Specifically, researchers should consider sampling strategies that increase sample sizes and incorporate different course modalities into analysis. Additionally, this study produced several noteworthy findings that are deserving of further review. More precisely, future research should continue to explore rational choice theory within the context of cheating research, new ways of measuring course quality among students, and behavioral distinctions among health science majors. As such, the directions for future cheating research can be broken into five categories: sampling, course type, rational choice theory, perceptions of course quality, and health science students.

As discussed above, researchers should first consider methods that improve generalizability within a study. One approach to improving generalizability in cheating research is to increase sample sizes and to survey students at multiple institutions. To increase the number of participants in a study, researchers should consider sampling methods that have historically higher response rates. In previous studies, stratified random sampling has been utilized for the data collection process (Freiburger et al., 2016; Vowell & Chen, 2004). This strategy involved random selection of class sections, where students completed surveys during their respective class periods. An added benefit to higher response rates is greater participant diversity within a

study. As discussed above, this study was overrepresented by students with high grade point averages. Had this survey achieved a higher participation rate across multiple college campuses, a greater mix of students may have comprised the sample.

Second, future research should examine academic dishonesty across multiple course types. In this study, the course type variable was split into two modalities: traditional and online. As such, this study excluded hybrid models that incorporate components of both traditional instruction and remote learning. In subsequent studies, academic dishonesty within hybrid courses should be integrated into analysis. For many colleges, hybrid courses are popular options for educational delivery (Bowen et al., 2014). Hybrid models incorporate components of both traditional and online learning, allowing institutions to enjoy several benefits from modalities. For example, hybrid courses still integrate in-person attendance for weekly classes. However, the remote learning component also alleviates challenges on a campus by freeing up classroom space and reducing student congestion on a campus (Bowen et al., 2014; Lanier, 2006). With the increased popularity in hybrid courses, future research should investigate cheating distinctions across traditional students, hybrid students, and fully online students.

Third, research should continue to explore rational choice theory within the context of academic dishonesty. As shown in this study, the variables for student perceptions of cheating costs & benefits were consistently significant within the quantitative analyses. The results indicate that students are significantly less likely to engage in academic dishonesty when the personal costs are higher. Since this current study examined multiple components related to rational choice theory, the costliness of cheating on student behavior was only partially explored. Greater focus on this research area could reveal promising results for the field of academic dishonesty. Specifically, further studies into the perceptions of cheating costs could have widespread implications for collegiate policy. Should costs & benefits variables prove

continuously significant, institutions may incorporate this research into student sanctions for academic dishonesty.

Fourth, researchers should further explore the impact of perceived course quality on student cheating behavior. As previously discussed, the quality variable was significant across various statistical models in this study. Specifically, students who had more favorable views of course quality displayed lower intentions to cheat. In general, perceptions of quality are an important variable to consider among modern educational research. With this new emphasis on online learning, students may be more critical of the education they receive. For this study, the measurement of the quality variable was a research limitation. More precisely, perceptions of course quality was measured through a single survey question. For future studies, researchers should consider the multiple factors that may influence a student's perception of course quality. In doing so, the impact of course quality on student academic behaviors can be better understood.

Lastly, academic dishonesty among health science majors should be further analyzed. During preliminary statistical analysis, unexpected findings concerning health science majors did become apparent. While this study initially suspected that criminal justice would engage in the lowest rates of cheating, this hypothesis was not supported in quantitative testing. Rather, health science majors displayed the lowest intentions for cheating when compared to other academic majors. In general, future researchers should investigate this finding more closely. For health science majors, lower intentions to cheat may derive from teaching strategies within these respective schools. Specifically, the topic of professional ethics may be strongly emphasized within health sciences courses. Should this prove accurate in subsequent research, faculty may find ways to interweave these disciplinary practices on ethics into criminal justice curriculum.

Conclusions

As a result of the 2020-2021 Covid-19 pandemic, the landscape of higher education has changed considerably. In adherence with public health recommendations, many colleges made significant adjustments to campus operations and course delivery. While continuity of education remained intact during this period, the impact of widespread remote learning on college student cheating remained relatively unknown. In response, this study sought to examine current cheating behaviors among online students and criminal justice majors. Overall, this research produced noteworthy findings for these two groups of students.

While online students were expected to exhibit higher likelihoods for academic dishonesty, their behaviors were fairly similar to those of traditional students. While some variance between the course groups were observed in test cheating and plagiarism, the results as a whole suggest a broad equivalence of cheating behaviors among all students. Similarly, criminal justice students also displayed similar behaviors to other academic majors. Unfortunately, certain findings also indicated higher likelihoods for certain forms of cheating. In general, these findings have notable implications for collegiate policy, specifically in decisions concerning online course delivery and criminal justice curriculum.

Furthermore, this study should provide an adequate framework for future research. Continued research into academic dishonesty among college students is quite relevant, especially with the current operations of higher education. Widespread cheating among college students negatively impacts the quality and credibility of collegiate institutions. Furthermore, these dishonest behaviors during college can have long-term implications, resulting in dishonest professional behaviors (Sims, 1993). To remedy these concerns, variables that increase student likelihoods for cheating must be actively investigated. Based on this study, factors such as course type, academic major, peer influences and perceptions of cheating benefits appear to influence

cheating behaviors among modern students. As universities continue to navigate through the pandemic, research should continue to explore how these factors influence cheating among students. By building on this research, colleges can better address the issue of cheating and develop initiatives that promote academic integrity among students.

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